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Abstract

Using experimental asset markets, we study the situation of a financial analyst who is trying to infer the fundamental value of an asset by observing the market's history. We find that such capacity requires both standard cognitive skills (IQ) as well as social and emotional skills. However, forecasters with high emotional skills tend to perform worse when market mispricing is high as they tend to give too much emphasis to the noisy signals from market data. By contrast, forecasters with high social skills perform especially well in markets with high levels of mispricing in which their skills could help them detect possible manipulation attempts. Finally, males outperform females in the forecasting task after controlling for a large number of relevant individual characteristics such as risk attitudes, cognitive skills, emotional intelligence, and personality traits.

Keywords: Forecasting, experimental asset markets, theory of mind, personality traits, cognitive skills.

JEL CODES: C92, G17, D91, G41.

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1. Introduction

Although fewer and fewer jobs involve direct trading of securities, a large number of tasks in the financial industry require understanding the economic implications of market prices. Forecasting is an essential part of the job of financial analysts and fund managers, as well as many professional economists (Elliott and Timmermann, 2008). However, this practical role of economists is in contradiction to the idea that markets are informationally efficient (Samuelson, 1965; Fama, 1965, 1970, 1991). If financial markets were informationally efficient, then no special skill would be needed to infer the current state of the economy from market prices. In the same vein, any success at forecasting market outcomes would simply be due to luck (Batchelor, 1990; Hartzmark, 1991; Barber and Odean, 2000; Malkiel, 2003; Qu, Timmermann and Zhu, 2019), which Kahneman (2011) refers to as an *illusion of skill*.

Nevertheless, few would disagree that actual markets are not perfectly efficient as was shown in both archival (e.g., De Bondt and Thaler, 1985, 1987; Lo and MacKinlay, 1988; Bernard and Thomas, 1990; Cutler, Poterba and Summer, 1991; Chopra, Lakonishok and Ritter, 1992; Jegadeesh and Titman, 1993, 1995; Shleifer, 2000; Lo, 2019) and experimental studies (e.g. Smith, Suchanek and Williams, 1988; Biais et al. 2005, Hanson, Oprea and Porter, 2006; Veiga and Vorsatz, 2010; Corgnet et al. 2018; Page and Siemroth, 2017, 2018; Corgnet, DeSantis and Porter, 2020a). In the presence of mispricing, market prices become noisy signals creating a situation in which accurate forecasting might require *genuine skills*. In that context, what skills would economists and financial analysts need to possess to provide accurate forecasts? Surprisingly little is known about the individual characteristics driving forecasting performance. This lack of knowledge could, of course, be due to the absence of such skills (Kahneman, 2011). But, the seminal work of Bruguier, Quartz and Bossaerts, 2010; BQB henceforth, identifies specific forecasting skills related to emotional intelligence. More specifically, BQB show that one's capacity to understand others' emotions (Baron-Cohen et al. 1997) and ascribe intentions to apparently random patterns (Heider and Simmel, 1944) are key predictors of forecasting performance in an experimental asset market in which insiders were sometimes present. These skills have been referred to as *theory of mind* (Frith and Frith, 1999) because they relate to one's inclination to build a mental model of others' behavior. The neurological study of BQB detected an activation in the paracingulate cortex, which is known to activate when inferring others' intentions, for those forecasters who successfully predicted the direction of price changes. BQB also collected some behavioral data showing a positive correlation between theory of mind skills and forecasting performance.

We aim to provide a more comprehensive assessment of the individual drivers of forecasting performance by extending the work of BQB, who only studied 43 participants in their behavioral experiment connecting theory of mind and reasoning test scores with forecasting performance. Using a larger sample, we assess the relative importance of theory of mind and other individual characteristics which were not studied by BQB, but have been found to explain financial behavior in archival or experimental studies. This includes standard cognitive skills, IQ (Raven, 1936) and cognitive reflection (Frederick, 2005), risk attitudes (Crosetto and Filippin, 2013) as well as personality traits (Ashton, Lee and de Vries, 2014). To accomplish our goal, we showed participants data from previously-conducted experimental markets. In these markets, traders bought and sold assets whose value depended on the state of the economy. The asset value was 50, 240 or 490 if the state of the economy was low, medium or high, respectively. Traders were endowed with private information which, in aggregate, was sufficient to reveal the true state. If markets are informationally efficient, then the asset's price should equal its value (Plott and Sunder, 1982, 1988). Participants were then asked to forecast the state of the economy using a quadratic scoring rule. In addition, we asked participants to make predictions in different settings in which we varied the type of market information that was displayed on the forecasters' screens. We then linked participants' forecasting performance to their individual characteristics.

Our main findings support the hypothesis that theory of mind skills play a fundamental role in accounting for a person's forecasting success. This result provides a strong robustness check for the findings in BQB because it was obtained with three times more observations than the original study and because we controlled for additional individual characteristics.[1]

[1] BQB's ex-post power for the correlations between forecasting performance and their two theory of mind measures are 0.50 and 0.63, respectively.

Our second main result extends BQB by showing that standard cognitive skills, in particular IQ, also contribute to explaining forecasting performance. This finding is in line with the archival study of high-performing forecasters, so-called "superforecasters" (Tetlock and Gardner, 2016), who were found to possess high IQ levels. In addition, social skills, as measured by the extraversion personality trait (Ashton, Lee and de Vries, 2014), help explain forecasting performance. This result is consistent with previous research showing a positive link between self-monitoring scores (Snyder and Gangestad, 1986), which is closely linked to the personality trait of extraversion (Furnham, 1989; Osborn, Field and Veres, 1998), and traders' earnings in double auctions (see Biais et al. 2005).

Our findings that standard cognitive skills, as well as emotional and social skills, explain forecasting performance support the hypothesis that forecasting skills are *real* and not *illusory*. In addition, we layout specific mechanisms by which forecasting skills operate challenging further the idea that forecasting performance is just luck.

2. Hypotheses

Predicting asset prices accurately requires specific skills related to theory of mind, as shown by BQB. They found that theory of mind skills measured with a Heider-Simmel task (Heider and Simmel, 1944) and the eye-gaze test (Baron-Cohen et al. 1997) were significant predictors of forecasting performance. In their behavioral setup, forecasters had to predict the direction of price changes in markets that could be populated by insiders or not. In BQB, the ability of traders to assess the direction of price changes accurately thus crucially hinges upon their capacity to attend and extract traders' private information. In related papers, Corgnet, DeSantis and Porter (2018) and Hefti, Heinke and Schneider (2018) have reported a positive effect of theory of mind skills on traders' performance in experimental asset markets. These authors stress that traders with high theory of mind skills perceive market orders and prices as resulting from traders' intentional actions. High theory of mind traders are thus especially attentive to market data and hence are more likely to extract valuable information from observed market activity.

Because the effect of theory of mind skills crucially hinges upon extracting private information from observed market data, these skills will be especially beneficial when mispricing in the market is low. By contrast, in markets with high mispricing, which is typical of markets where traders possess imprecise private information (Corgnet, DeSantis and Porter, 2020a), forecasters will not be able to learn much from market data. In the case of asset market bubbles where mispricing is particularly high, De Martino et al. (2013) show that theory of mind skills can be detrimental. Forecasters possessing high theory of mind skills tend to actively use market data and mistakenly infer information about the value of an asset from meaningless trends instead of recognizing that the market is driven by noise. This negative effect of theory of mind is also highlighted by Hefti, Heinke and Schneider (2018), who refer to market participants engaging in such behavior as being "semiotic."

Theory of mind skills closely relate to pattern recognition. Thus, high theory of mind traders tend to be influenced by market trends even when these trends do not reflect private information. A critical feature of the market that sustains this effect is the graphical display of market orders on the trading screen. This feature is often included in trading platforms such as the setup of De Martino et al. (2013). When real-time charts and orders are available on the screen, they prompt pattern recognition (Lo, Mamaysky and Wang, 2000; Lo and Hasanhodzic, 2011), especially for people who possess high theory of mind (De Martino et al. 2013). It follows that theory of mind skills might hurt forecasting performance in cases in which both the graphical display of market orders is available to forecasters and mispricing levels are high. This leads to Hypothesis 1.

Hypothesis 1 (Theory of Mind & Forecasting Performance)

i) Theory of mind skills will enhance forecasting performance when mispricing is low.

ii) Theory of mind skills will hurt forecasting performance when mispricing is high and the graphical display is complete.

Our next hypothesis assesses the predictive power of cognitive skills in explaining forecasting performance. In particular, we focus on IQ and cognitive reflection because both have been found to explain financial performance consistently. IQ (or fluid intelligence) which measures one's capacity to perform abstract mental calculations (Mackintosh and Mackintosh, 2011) has been shown to relate to stock market participation and successful investment decisions (Kezdi and Willis, 2003; Cole and Shastry, 2009; Christelis, Jappelli, and Padula, 2010; Grinblatt, Keloharju, and Linnainmaa, 2011; Benjamin, Brown, and Shapiro, 2013). Using a unique database of adult Finnish men, Grinblatt, Keloharju, and Linnainmaa (2012) found that high-IQ people exhibited better market timing than their low-IQ counterparts, thus being more likely to buy winning stocks and sell losing stocks. In experimental asset markets with private information similar to the ones used in the current study, Corgnet, DeSantis and Porter (2018) show that high-IQ traders earned significantly more than low-IQ traders.[2] Higher IQ test scores have also been found to correlate with fewer Bayesian updating errors (Charness, Rustichini, and van de Ven 2018; Corgnet, DeSantis and Porter, 2018) and with higher levels of strategic reasoning (Civelli and Deck, 2018).[3] We thus predict that greater fluid intelligence should help forecasters infer the true asset value given market observables.

At first, this prediction might seem at odds with the finding of BQB that participants' scores on a reasoning task did not significantly explain forecasting performance. However, our forecasting task differs from BQB as they asked participants to predict the direction of price changes in the market. Instead, we ask them to uncover the true asset value based on market data. Our task thus requires Bayesian inference whereas theirs might not (see Corgnet, DeSantis and Porter, 2018). It follows that fluid intelligence, which is necessary for this type of inference, will help in predicting the state accurately. It is also interesting to highlight that the reasoning task used in BQB is not a measure of IQ but rather of cognitive reflection (or inhibitory control, Diamond, 2013).[4] The null result of BQB regarding the predictive power of inhibitory control in their forecasting task might suggest cognitive reflection scores will not significantly predict forecasting performance in our setting. However, many experimental papers have stressed the predictive power of CRT scores on traders' performance (see Breaban and Noussair, 2015; Corgnet et al. 2015; Noussair,

[2] Similar results are found by Hefti, Heinke and Schneider (2018) using the canonical design of Smith, Suchanek and Williams (1988) for exploring price bubbles in asset markets.

[3] High-IQ people have also been shown to induce greater truthful revelation in second price auctions (Lee et al. 2020).

[4] Although cognitive reflection scores correlate positively with IQ scores, both constructs are distinct because they relate to different executive functions. IQ can be seen as a measure of working memory whereas cognitive reflection relates to inhibitory control (Stanovich, 2011; Stanovich, 2016).

Tucker and Xu, 2016; Hanaki et al. 2017; Duchêne et al. 2019; Corgnet, DeSantis and Porter, 2020a; Schneider and Porter, 2020). Similar to IQ scores, CRT scores have also been shown to positively relate to one's ability to apply Bayes' rule adequately (Oechssler, Roider and Schmitz, 2009; Hoppe and Kusterer, 2011; Toplak, West and Stanovich, 2011; Corgnet, DeSantis and Porter, 2018). Because Bayesian updating is key to inferring private information from market observables and thus inferring the true state, cognitive reflection should enhance forecasting performance. Yet, we might expect CRT scores to be less predictive of forecasting performance than IQ scores given the findings in BQB. One potential reason why cognitive reflection might play a lesser role in a forecasting task than in a trading task is that forecasters are explicitly instructed to interpret what is occurring in the market as opposed to traders who have to realize for themselves the value of forecasting for making profitable trades.[5]

Similarly to theory of mind skills, the positive impact of standard cognitive skills on forecasting performance hinges upon extracting private information from market data. It follows that these skills will be especially relevant when individual traders possess a large amount of private information, and mispricing is low. Unlike theory of mind skills, standard cognitive skills have not been shown to induce pattern-following behaviors in the absence of relevant private information (Hefti, Heinke and Schneider, 2018). Thus, we do not expect fluid intelligence to hurt forecasting when mispricing is high.

Finally, we do not expect the graphical display to have a major influence on the forecasting decisions of people possessing high standard cognitive skills. More generally, people with high CRT and IQ scores are less influenced by the framing of information when making decisions (Frederick, 2005; Toplak, West and Stanovich, 2011; Fosgaard, Hansen and Wengström, 2017). Unlike people possessing high theory of mind skills, we do not expect the graphical display of information to prompt pattern-recognition behaviors in people possessing high standard cognitive skills. We thus expect the graphical display of

[5] More generally, cognitive reflection measures how much attention one pays to a task. A tendency to reflect on a task is less important when one's has been explicitly directed to focus one's attention on the particular task.

information not to moderate the effect of standard cognitive skills on forecasting performance. This leads to Hypothesis 2.

Hypothesis 2 (Standard Cognitive Skills & Forecasting Performance)

i) Fluid intelligence, and to a lesser extent cognitive reflection, will enhance forecasting performance when mispricing is low, regardless of the graphical display of information available to forecasters.

ii) Standard cognitive skills will not enhance forecasting performance when mispricing is high, regardless of the graphical display of information available to forecasters.

The finance literature has generally ignored personality traits despite recent works showing their relevance in explaining individual economic success (see Borghans et al. 2008; Barrick and Mount, 2009; Almlund et al. 2011; Heckman and Kautz, 2012; Corgnet, Hernan and Mateo, 2015). The experimental economics literature has also shown correlations between personality traits and strategic sophistication (Gill and Prowse, 2016). The authors show that agreeable and emotionally stable people tend to be more strategically sophisticated in beauty contest games because they played numbers closer to the Nash equilibrium.

Only a few papers have studied the impact of personality traits on traders' earnings and strategies in experimental markets. One such study, Biais et al. (2005), shows self-monitoring explains traders' performance.[6] More specifically, Biais et al. (2005, p. 298) claim that people who score high on self-monitoring "may assume that other market participants are also behaving strategically and trying to manipulate the market as they do. Accordingly, high self-monitors should be less likely to take market prices at face value, and will reason about the signals and strategies that generated them." Even when traders are not explicitly incentivized to manipulate prices (as in Hanson, Oprea and Porter, 2006), they can place orders that contradict their private information so as to distort prices and thus trade advantageously (Biais et al. 2005). Self-monitoring skills are likely to be especially critical in markets in which mispricing is high and attempts to distort prices are

[6] Snyder and Gangestad (1986) refer to self-monitoring as a stable personality trait which is defined as one's inclination to attend social cues.

likely. By definition, markets with low mispricing have not experienced successful manipulation attempts, and as such, self-monitoring is unlikely to help forecasters. By contrast with theory of mind and standard cognitive skills, self-monitoring will lead traders to downplay the role of prices as valuable signals of the true asset value.

Self-monitoring closely relates to extraversion, one of the five fundamental personality traits (Lippa, 1976; John, Donahue, and Kentle, 1991; John, Naumann and Soto, 2008; Ashton, Lee and de Vries, 2014). Heckman and Kautz (2012) define extraversion as "an orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience, characterized by positive affect and sociability." Self-monitoring has been found to correlate positively and substantially with extraversion (see Furnham, 1989; Osborn, Field and Veres, 1998) whereas other personality traits such as conscientiousness, openness, agreeableness or neuroticism have not.

Interestingly, the only personality trait that has been shown to correlate positively with portfolio earnings of individual investors is extraversion (Lo, Repin and Steenbarger, 2005; Durand, Newby and Sanghani, 2008). Using the data from these studies, we show that individual investors score particularly high on extraversion compared to a large sample of adults and university students (see Appendix A). This suggests extraversion might play an important role in investors' success. In this study, we decided to measure extraversion instead of self-monitoring because of its broader use and its psychometric properties (Lee and Ashton, 2004).

Finally, the effect of extraversion is unlikely to be affected by the graphical display of information. This is the case because extraversion, unlike theory of mind skills, does not relate to one's inclination for reading patterns. For example, extrovert forecasters who observe a rising price trend will not infer a high asset value if they correctly believe traders are manipulators or trend-followers who place orders based on something other than private information (Biais et al. 2005). The final hypothesis summarizes our predictions regarding extraversion.

Hypothesis 3 (Extraversion & Forecasting Performance)

i) Extraversion will enhance forecasting performance when mispricing is high, regardless of the graphical display of information available to forecasters.

ii) Extraversion will not enhance forecasting performance when mispricing is low, regardless of the graphical display of information available to forecasters.

Our hypotheses contribute to the current literature by establishing distinct mechanisms by which individual drivers of financial behavior such as emotional skills, cognitive ability, and personality traits might operate. We test these mechanisms in a laboratory setting in which we can manipulate mispricing levels in markets and the graphical display of information available to forecasters.

3. Design

The experiment was conducted in three phases: Instructions, Forecasting Task and Questionnaire. The full set of instructions is available in Appendix B.

3.1. Instruction phase

The participants were recruited from a pool of individuals who had previously traded in an experimental asset market in the style of Plott and Sunder (1982 or 1988).[7] In Phase 1, the participants were reminded that they had previously participated in a relevant market experiment in which a single asset was traded for 5 minutes. This asset paid a liquidating dividend of either 50, 240, or 490 at the end of the market period with probabilities commonly known among the 12 traders in the market. Private signals of the form “Not 50”, “Not 240”, and “Not 490” were available to the traders in these markets. In Plott and Sunder (1982)-style markets, some traders were *fully-informed* meaning they were given two of these signals at the beginning of the period so that they knew the true asset value with certainty. The other traders were *uninformed* in that they did not receive private signals. In Plott and Sunder (1988)-style markets, all traders were *partially-informed,* meaning that each received exactly one private signal, but half received one signal and the

[7] We recruited participants who were experienced in trading to ensure they would understand the financial environment in which they had to make forecasts.

other half received the other possible signal. Thus, in aggregate, the participants had complete information.

Participants were given a reminder of how the double auction trading market worked as well as the basic private signal and asset value structures. They completed two unpaid practice markets lasting five minutes. In the first practice market, participants were informed that all traders would be *partially informed*. In the second practice market, they were informed that one-half of the traders would be *fully informed*. As in the historic markets, these markets were conducted with groups of 12 participants. At the conclusion of the second practice market, participants were informed that they would be shown past experimental sessions and be asked to make inferences about what they observed. An incentivized three-question comprehension quiz was then administered ($0.50 per correct answer). Upon completion of the quiz, a monitor read the solutions to the participants and publicly answered any questions.

3.2. Forecasting task

In Phase 2, participants were placed in the role of a forecaster observing data from a previous financial market experiment (market data taken from Corgnet, DeSantis, and Porter, 2018 and 2020a).[8] The forecasters' main task was to predict the true value of the asset being traded in the observed markets.

Of the available data from Corgnet, DeSantis, and Porter (2018 and 2020a), 12 sessions were randomly selected: four (out of 10) of the sessions in which there were 12-*partially informed* traders, four (out of 10) of the sessions in which there were 6-*fully informed* traders, and four (out of 5) of the sessions in which there were only 2-*fully informed* traders.[9] Five market periods were then randomly drawn from each of these sessions. These five market periods from a single historic session were grouped together and treated as a single "block." The ordering of the blocks (five periods from a historic session) and the ordering of the markets within a block were randomized for each participant. That is, each participant observed a (different) random sequence of the 12 historic sessions listed above.

[8] Due to a recruitment error, six of the 125 participants in the current study actually participated in Corgnet, DeSantis, and Porter (2018 or 2020a).

[9] The parentheses report the number of historic markets of the given type that were conducted by Corgnet, DeSantis, and Porter (2018 and 2020a).

Moreover, each participant observed a (different) random sequence of the five markets within each historic session. That said, all participants observed data from the same 60 market periods.

Participants forecast the true asset value for each market they observed by assigning a probability, $Prob_v$, to each of the three possible asset values: $v \in V \coloneqq \{50,\ 240,\ 490\}$.[10] Upon conclusion of a block, participants were asked to forecast two additional characteristics of the original session from which the five (just observed) markets were drawn. First, participants assigned probabilities to each of the three possible information structures: 12-*partially informed*, 6-*fully informed*, and 2-*fully informed*. Second, participants assigned probabilities to the number of participants in the original session who had high CRT scores.[11] In addition to allowing us to examine forecasters' beliefs about the group of traders they just observed, this served to reinforce to the forecaster that each block of five markets was from a distinct group of traders.

A quadratic scoring rule was used for each elicited belief (60 forecasts of true asset value, 12 forecasts of information structure, and 12 forecasts of CRT level). The payment per question was determined via the following equation:

$$\frac{1}{2}\left[1 + 2 \times Prob_{correct} - \sum\nolimits_{v \in V} Prob_v^2\right]$$

where $Prob_{correct}$ is the probability the forecaster assigned to the true asset value. Thus, the payment per question could range between \$0.00 for a guess that placed all probability on an incorrect value and \$1.00 for a guess that placed all probability on the correct value, while placing equal weight on all values would result in a payoff of \$0.67. Participants were informed of the correct answer after submitting a forecast. Thus, they received immediate feedback regarding the accuracy of their forecast.

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[10] In addition to the market activity, forecasters were given the same commonly known probabilities (35%, 45%, and 20%) as the traders about the asset being worth 50, 240, or 490.

[11] Corgnet, DeSantis, and Porter (2018 and 2020a) administered a seven-question CRT survey to participants in the original sessions. Our forecasters were asked to predict how many of the original traders answered at least four of the seven CRT questions correctly: 0 to 4, 5 to 8, and 9 to 12. Our forecasters were provided with the CRT questions prior to making this prediction.

3.3. Questionnaire

In Phase 3, participants completed a series of six surveys: (1) Heider-Simmel Test, (2) Cognitive Ability Test, (3) Bomb Risk Elicitation Task, (4) Eye-Gaze Test, (5) HEXACO Personality Test, and (6) Demographic Questions. Because each of the subjects participated as a trader in a previous market experiment in which the CRT was administered, we used the previously collected score instead of re-administering the test.[12]

The Heider-Simmel Test (HS test, henceforth) is one of the two tasks which have commonly been used to assess theory of mind skills (Bossaerts, Suzuki and O'Doherty, 2019). It was operationalized in a manner similar to Bruguier et al. (2010). Participants watched a video in 5-second intervals of three geometric objects: a circle and two triangles. After each interval, the video was paused for 10 seconds, and participants were asked to forecast whether, after the next 5-second interval, the large triangle was going to be closer to, farther from, or at the same distance from the small triangle. Participants were paid $1 for each correct answer and incurred a $0.25 penalty for not responding within the 10 seconds. Participants made a maximum of 14 guesses in this task.

The Cognitive Ability Test (Intelligence test, henceforth) was adapted from Civelli and Deck (2018). In this test, participants were shown a three-by-three table of images with the image in the lower right corner missing. Participants were asked to select the image (from a given set of images) that logically completes the pattern similarly to the Raven (1936) test. Participants were given six minutes to answer 12 such questions. Each correct answer was worth $0.50.

The Bomb Risk Elicitation Task (BRET, henceforth) is adapted from Crosetto and Filippin (2013).[13] In this test, participants were shown a seven-by-seven square grid of boxes. A bomb was randomly placed behind one of the 49 boxes. Participants were instructed to select a number between 1 and 49, indicating the number of boxes they wished to collect

[12] Corgnet, DeSantis and Porter (2015) administered the CRT at the conclusion of their experimental sessions. The authors note that some of their participants had previously taken the CRT. They do not find significant differences between these individuals' two scores. Thus, the decision was made to reduce the length of the overall experiment rather than recollecting the CRT measure from the participants.

[13] We opted for this risk elicitation tool because it provides a granular partition of risk attitudes while only requiring a single decision. Tasks that involve more questions can yield data inconsistent with standard models of risk or impose structure on the decision maker.

(collection occurred left to right then top to bottom). If the bomb was behind one of the collected boxes, then the participant earned $0.00 for this task. If the bomb was not behind one of the collected boxes, then the participant earned $0.10 for each collected box. Participants were given two minutes to complete this task. Even though we do not have a specific hypothesis regarding the effect of risk attitudes on forecasting performance, we included it as a control. Risk attitudes have been shown to relate to financial behavior in experimental markets accounting for lower bids on risky assets (e.g. Fellner and Maciejovsky, 2007; Breaban and Noussair, 2015).

The Eye-Gaze Test is adapted from Baron-Cohen et al. (1997) and is another task commonly used to assess theory of mind skills. Participants were shown ten sets of eyes (Olderbak et al. 2015) and instructed to select the word (from a list of four) that best described what the person in the image was thinking or feeling.[14] Because Baron-Cohen et al. (1997) provide a list of correct answers which had been previously validated, we can calculate a performance score for this test. Participants were given six minutes to complete this task, which was not incentivized.[15]

The HEXACO Personality Test asks participants to decide on a scale of 1 (strongly disagree) to 5 (strongly agree) how much they agreed with each of several statements.[16] This survey assesses 6 major dimensions of personality (Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness, and Openness to Experience).[17] Participants were given 10 minutes to complete the 60 questions.

Demographic Questions consisted of the following three items: (1) What is your gender? (2) Do you regularly look at stock prices? (3) In what school are you enrolled?

[14] This is a short version of the original 36-item test. But, Corgnet, DeSantis, and Porter (2018 and 2020a) administered the full-version of the eye-gaze test in the original sessions so that we also have this score in our database. In the results section, we use the 36-item score although no significant differences are found when using the 10-item version.

[15] Although it is standard not to incentivize this test (Baron-Cohen et al. 1997; Corgnet, DeSantis and Porter, 2018), BQB paid for performance.

[16] See http://hexaco.org/hexaco-inventory for more details regarding the HEXACO personality test.

[17] Although the literature does not suggest any hypotheses regarding the predictive power for personality traits beyond extraversion, we decided to measure all traits. This is first motivated by the methodological concern of conducting the HEXACO test in its standard form rather than isolating a subset of questions. Second, this allows us to test whether the predictive power of extraversion continues to hold when controlling for other personality traits (see for example, Appendix C, Table C4).

3.4. Treatments

We utilized a 3×4 factorial design to test our three hypotheses. To that end, the design exogenously manipulates the structure of information to induce different levels of mispricing (within-subject design on 3 levels). It also varies the graphical display of information presented to forecasters (between-subject design on 4 levels). With either 31 or 32 forecasters per graphical display each making 20 forecasts for each of 3 information structures, we observe a total of 7,500 forecasts for an average of 625 forecasts per combination of graphical display and information structure.

3.4.1. Mispricing

Mispricing was exogenously manipulated in each experimental session by having participants make forecasts under three possible information structures: 12-*partially informed*, 6-*fully informed*, and 2-*fully informed*. Corgnet, DeSantis and Porter (2020a) show that prices closely track fundamentals in markets where one-half of the traders are insiders (6-*fully informed*). In contrast, private information is not aggregated in the 12-*partially informed* and 2-*fully informed* markets. In related experiments, Bossaerts, Frydman and Ledyard (2014) show that mispricing decreases as the number of fully-informed traders in the market increases.[18] To assess mispricing, we calculate the average across markets of the mean absolute deviation (MAD) between the price and the true asset value. MAD values are similar for the 12-*partially informed* and 2-*fully informed* markets (averages of 147.899 and 155.020, respectively, and p-value = 0.871 from the Wilcoxon Rank Sum Test), and both are significantly higher than the MAD values for the 6-*fully informed* markets (average of 60.031, p-values<0.001 for the two pairwise comparisons using Wilcoxon Rank Sum Tests). In the subsequent analysis, we will conduct a median split of markets based on MAD, and using markets with different information structures assures considerable heterogeneity of MAD across all markets.

3.4.2. Graphical display

The second design dimension corresponds to the nature of the graphical display shown to the forecasters. There were four variations of a forecaster's screen based upon

[18] One major difference with our setup is that they explicitly allow for gains from exchange.

combinations of two distinct features (see Figures B1 to B4 in Appendix B). The order book, which displays bids and asks (see Offers to Sell and Offers to Buy on the right side of Figure B1 in Appendix B), was either visible (*Book* treatments) or not visible (*No Book* treatments). The market charts were either displayed dynamically (*Dynamic* treatments) or statically (*Static* treatments). In *Dynamic* treatments, the participants observed a time-compressed 30-second video replay of the market that originally lasted for 5 minutes. In *Static*, the participants were shown the final image from the market replay video for 30 seconds. While forecasters could assign probabilities for each possible true asset value at any point during the 30-second observation window, they could not submit the probabilities until the 30 seconds had elapsed.

In total, we had four different treatments varying the graphical display of information: *Dynamic* – *Book, Dynamic* – *No Book, Static* – *Book,* and *Static* – *No Book*. Given the specifics of our experimental design, we derive the following predictions based on our three hypotheses.

3.5. Predictions

Table 1 summarizes the relationship between our design and hypotheses. Hypothesis 1 puts forth that theory of mind skills will boost forecasting performance when mispricing is low, and the graphical display of information available to forecasters is complete (see cell *Dynamic – Book* & 6-*fully informed* in Table 1). By contrast, Hypothesis 1 posits a negative effect of theory of mind skills when mispricing is high and the graphical display of information available to forecasters is complete (see cell *Dynamic – Book* & *12-partially informed / 2-fully informed* in Table 1). For the rest of the cases, we do not state a directional prediction for the effect of theory of mind skills on forecasting performance.

Hypothesis 2 posits that standard cognitive skills will boost forecasting performance when mispricing is low regardless of graphical display (see low mispricing cells in Table 1) whereas no effect is expected for high mispricing levels.

Hypothesis 3 emphasizes that extraversion will boost forecasting performance when mispricing is high regardless of graphical display (see high mispricing cells in Table 1) whereas no effect is expected for low mispricing levels.

Although the 12-*partially informed* and 2-*fully informed* treatments differ in the structure of information, they exhibit identical mispricing (Corgnet, DeSantis and Porter, 2020a). Because our conjectures emphasize mispricing rather than information structure as a key driver of the impact of individual skills on forecasting performance, we do not expect differences between these two treatments (see Table 1). However, we decided to include both in our design to provide an additional robustness check.

Table 1. Predictions for each treatment

Mispricing / **Graphical display**	**Low** 6-*fully informed*	**High** 12-*partially informed* 2-*fully informed*
Incomplete *Static – No Book*	Theory of mind **(=)** Intelligence & CRT **(+)** Extraversion **(=)**	Theory of mind **(=)** Intelligence & CRT **(=)** Extraversion **(+)**
Intermediate *Dynamic – No Book* *Static – Book*	Theory of mind **(=)** Intelligence & CRT **(+)** Extraversion **(=)**	Theory of mind **(=)** Intelligence & CRT **(=)** Extraversion **(+)**
Complete *Dynamic – Book*	Theory of mind **(+)** Intelligence & CRT **(+)** Extraversion **(=)**	Theory of mind **(-)** Intelligence & CRT **(=)** Extraversion **(+)**

Each cell corresponds to a level of mispricing and a level of graphical display. Signs (+ / - / =) refer to whether a given set of skills (theory of mind, intelligence & CRT, and extraversion) will enhance / hinder / leave unaffected forecasting performance in a given cell.

3.6. Procedures

A total of 125 participants completed this study in 6 sessions. The average earnings of the participants were $49.85.[19] This includes average payments of $0.66 for the

[19] The exchange rate was 1 experimental dollar equals US$ 1 in sessions 1 and 2 (12 and 24 participants). It was 1 experimental dollar equals US$ 0.50 in sessions 3 through 6 (24 participants in sessions 3, 4 and 5, and 18 in session 6). This exchange rate adjustment was made to keep average earnings in the range dictated by lab policy. In our analyses, we include session fixed effects which control for differences in exchange rates as well as other idiosyncratic session-specific shocks.

comprehension quiz in Phase 1, $33.95 for Phase 2 (forecasting task), and $8.24 for Phase 3 (questionnaire). In addition, participants were given a $7 participation payment for the 2-hour study.

Each experimental session was conducted with either 12 or 24 participants, and each participant was randomly assigned to one of the four between-subject treatments (*Dynamic* – *Book*, *Dynamic* – *No Book*, *Static* – *Book* and *Static* – *No Book*) conditional on the number of people in a session assigned to a treatment being equal.[20] This ensures that the observations are balanced across treatments and it reduces any impact of session effects on treatment effects.

Participants were drawn from a pool of approximately 670 participants at the Economic Science Institute at Chapman University who had previously participated in a Plott and Sunder (1982 or 1988)-style market.[21]

4. Results

We start by providing a correlation matrix for our main predictors of forecasting performance: theory of mind skills (as measured with the HS and the eye-gaze tests), standard cognitive skills (as measured with the intelligence test and the CRT) and extraversion.

[20] One session was run with 18 participants in which case the treatment assignment was not fully balanced. For the practice market periods, these participants were divided into two groups of nine. In session 5, one of the 24 participants exited halfway through Phase 2 of the experiment so that we had to drop this observation from the analyses.

[21] While the historic data used in this experiment closely followed the designs of Plott and Sunder (1982,1988), some of our participants had participated in variations of these markets in which traders had the ability to either purchase signals (Corgnet et al. 2018) or chat with other participants (Corgnet, DeSantis and Porter, 2020b).

Table 2. Correlations (p-values) between individual skills

	HS	Eye-gaze	Intelligence	CRT
Eye-gaze	-0.094 (0.297)	1		
Intelligence	-0.039 (0.663)	0.084 (0.351)	1	
CRT	**0.248** **(0.005)**	0.061 (0.501)	**0.318** **(0.0003)**	1
Extraversion	0.152 (0.091)	-0.159 (0.077)	-0.029 (0.748)	-0.104 (0.248)

In line with previous research, the correlation between CRT and intelligence score is positive and significant (see e.g. Toplak, West and Stanovich, 2011; Corgnet, DeSantis and Porter, 2018). The point estimate of 0.318 is very close to the correlation of 0.35 between CRT score and intelligence reported in Corgnet, DeSantis and Porter (2018). Toplak, West and Stanovich (2011) report correlation coefficients of 0.32 and 0.33 when looking at the relationship between other measures of fluid intelligence and CRT scores. The other significant correlation coefficient is the one between CRT and HS scores. Correlation between these variables has not been previously reported in the literature to the best of our knowledge. The absence of correlation between the eye-gaze test and CRT is also consistent with Corgnet, DeSantis and Porter (2018). Also, in line with BQB, we report a small and insignificant correlation between performance on the eye-gaze and HS tests.[22] As is highlighted by Bossaerts, Suzuki and O'Doherty (2019, p. 193), the two tests differ because, unlike HS, the eye-gaze test is not merely ''as if'' since it displays actual intentionality. By contrast, the HS test represents a situation in which the intentionality ascribed to the movement of geometric shapes is only "as if". Bossaerts, Suzuki and O'Doherty (2019) also posit that the HS test more closely represents the flow of transactions in a market setting because "(…) while each subject could be considered intentional, the result of their interactions is not." We also note that the mean score for each of the five skills listed in Table 2 did not differ between the Incomplete, Intermediate,

[22] BQB report a correlation coefficient ρ = 0.019 (p-value = 0.904). Hefti, Heinke and Schneider (2018) report a significant yet similarly small correlation coefficient between the two tests: ρ = 0.051.

and Complete graphical display treatment groups, which is the only dimension of the experimental design that was administered between-subjects.[23]

Next, we move to forecaster performance. Table 3 reports the average forecasted expected value of the asset conditional on the actual true value by the combination of graphical display and mispricing. Table 3 shows that forecasts systematically increased in the true asset value, thus reflecting that forecasters were able to extract valuable information from the market. This is a necessary condition for individual skills to matter in explaining forecasters' performance. Not surprisingly, forecasts more accurately reflected the true asset value in markets with low levels of mispricing.

Table 3. Average forecasted expected value of the asset for each treatment when the true asset value is (50, 240, 490)

Mispricing / Graphical display	**Low** 6-*fully informed*	**High** 12-*partially informed* 2-*fully informed*
Incomplete *Static – No Book*	(114.94, 254.92, 410.06)	(233.48, 268.10, 281.63)
Intermediate *Dynamic – No Book* *Static – Book*	(101.95, 244.71, 417.20)	(227.58, 255.59, 276.95)
Complete *Dynamic – Book*	(107.48, 250.15, 405.52)	(232.57, 257.58, 265.90)

We define two measurements of forecasting performance. We refer to the *price forecasting error* as the difference (in absolute terms) between the predicted expected value of the asset based on the probabilities reported and the true asset value. Our alternative forecasting performance measure is referred to as the *weight forecasting accuracy* and is equal to the weight the forecaster assigned to the true state (50, 240 or 490).

In our statistical analyses, we conduct panel regressions with subject random effects and fixed effects for session (1 to 6) as well as decision period (1 to 60).[24] We used robust

[23] Specifically, regression analysis yields p-values > 0.15 when testing that mean scores are the same across graphical display treatments for each of the five individual skills.

standard errors at the individual level. In total, we collected 7,500 observations corresponding to 125 forecasters making 60 decisions each.[25] We run separate regressions for each characteristic to avoid issues of collinearity due to the large correlation coefficients, as reported in Table 2, between CRT and intelligence scores, and between CRT and HS scores.[26] Each of the dummy variables in our regression tables take the value of 1 if the given characteristic was present for an individual forecast and takes the value of 0 otherwise. For example, the "Book Dummy" variable takes value 1 if a forecaster's screen displayed the book of orders, while "Two Insiders Dummy" takes value 1 if the market was populated by two fully-informed and 10 uninformed traders.

Table 4 reveals that pooling over all treatments, each of the individual characteristics significantly predicts price forecasting performance, except for the eye-gaze test.[27] In BQB, the predictive power of the eye-gaze test was significant though smaller in magnitude than HS. Taken together, these results suggest theory of mind skills related to pattern recognition (HS) are critical for explaining forecasting performance whereas theory of mind skills related to the reading of emotions (eye-gaze scores) are not. Regarding CRT, its predictive power is only marginally significant (see regression (2)) and its standardized coefficient is about 30% smaller than the coefficients for intelligence, HS, and extraversion. In addition, we note that men outperform women in all the regressions in Table 4, and this result is generally robust to alternative specifications (see Appendix C). In particular, we show that the gender effect is robust to controlling for various individual characteristics such as personality traits and risk attitudes (see Table C4). The size of the gender effect is, however, moderate (Cohen's d = 0.32 (0.39) for price forecasting error (weight forecasting accuracy)). Finally, forecasting performance is generally worse in markets in which mispricing is high (see positive (negative) and significant coefficient for "Two Insiders Dummy" ("Six Insiders Dummy")), the true asset value is high (see positive and significant

[24] Because of space constraints, we do not provide the coefficient estimates for these fixed effects. Importantly, decision period fixed effects do not show evidence of learning over the course of the experiment.
[25] Due to a programming error, a total of six observations were lost, two forecasts from each of three forecasters. Therefore, subsequent analyses rely on 7,494 observations.
[26] In Appendix C, we extend these analyses to the case in which all characteristics are included in a single regression (see Tables C2 and C3).
[27] Table C2 in Appendix C repeats this analysis with each individual characteristic simultaneously. In that specification only intelligence score and extraversion remain significant.

coefficient for "Asset Value") and the graphical display is complete (see positive and significant coefficient for "Book & Dynamics Dummy").[28]

Table 4. Price forecasting error as predicted by individual characteristics separately

VARIABLES	(1)	(2)	(3)	(4)	(5)
Intelligence score (std)	**-2.34****				
	(1.15)				
CRT score (std)		**-1.60***			
		(0.96)			
HS score (std)			**-2.18****		
			(1.11)		
Eye-gaze score (std)				**0.66**	
				(1.25)	
Extraversion (std)					**-2.24****
					(0.96)
Male Dummy	-4.90**	-4.20*	-4.86**	-4.41*	-4.12*
	(2.33)	(2.41)	(2.40)	(2.40)	(2.32)
Book Dummy	-1.96	-2.24	-1.85	-1.87	-1.54
	(3.28)	(3.30)	(3.21)	(3.27)	(3.30)
Dynamics Dummy	-0.24	-0.69	-0.31	-0.38	-0.69
	(2.74)	(2.72)	(2.70)	(2.77)	(2.73)
Book & Dynamics Dummy	9.16**	9.34**	8.22*	8.44*	8.01*
	(4.33)	(4.35)	(4.31)	(4.31)	(4.30)
Two Insiders Dummy	15.01***	15.01***	15.01***	15.01***	15.02***
	(1.93)	(1.93)	(1.93)	(1.93)	(1.92)
Six Insiders Dummy	-87.81***	-87.81***	-87.81***	-87.81***	-87.81***
	(2.01)	(2.01)	(2.01)	(2.01)	(2.01)
Asset Value	0.12***	0.12***	0.12***	0.12***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	103.77***	104.57***	105.26***	104.21***	103.75***
	(9.04)	(9.16)	(9.29)	(9.14)	(9.09)
Observations	7,494	7,494	7,494	7,494	7,494
R-squared	0.226	0.225	0.226	0.225	0.226
Chi-squared	6,170	6,283	6,223	6,135	6,129

Robust standard errors in parentheses with session and time fixed effects included as well as random effects for each subject. (std) indicates a standardized variable. *** p<0.01, ** p<0.05, * p<0.1.

[28] The negative effect of the complete graphical display on forecasting performance might seem counterintuitive. However, Hypothesis 1 suggests this could be due to the negative effect of theory of mind skills on forecasting performance when mispricing is high and the graphical display is complete.

In Table C1 in Appendix C, we report similar results using our alternate measure of forecasting performance (weight forecasting accuracy) with the exception that the coefficient associated with CRT becomes insignificant (p-value = 0.185). In Appendix C, we also provide robustness checks for these results. In particular, we conduct regressions in which all predictors are included so as to assess the relative predictive power of each individual characteristic (Tables C2 and C3). In line with previous findings, intelligence, HS and extraversion appear to have consistent explanatory power for forecasting performance. We also show that our findings continue to hold when adding individual controls, such as personality traits (HEXACO), and risk attitudes (BRET) (see Table C4). None of these additional controls predict forecasting performance, but the general patterns observed in Table 4 remain. In addition, our findings hold when using median splits (see Tables C5 to C8) and quartiles (see Tables C9 to C12) to define individual skills.

Finally, we show that the predictors of forecasting performance continue to be significant even after controlling for market characteristics such as average price and trading volume (see Table C13 in Appendix C).[29] This means that individual characteristics can help forecasters predict the true asset value better than a simple statistical model based on market observables. Interestingly, the relative importance of extraversion as a predictor of forecasting performance compared to HS and intelligence scores increases when controlling for market variables. Indeed, the standardized coefficients for HS and intelligence scores decrease by about 10 to 15% whereas the coefficients for extraversion increase by about 15% (see coefficients in Table C13 and Tables C2 and C3, regression (3)). This observation is consistent with the fact that, as is argued in our hypotheses section, the predictive power of theory of mind and intelligence scores rely upon accurately inferring the true asset value from market observables. Thus, controlling for market variables should automatically lower the incremental predictive power of theory of mind and intelligence test scores. By contrast, the predictive power of extraversion does not readily depend on inferring private information from prices but on the ability to identify attempts to distort prices and discard noisy signals. Because a simple statistical model of market observables

[29] We consider all the predictors which are significant in Tables C2 and C3, which is where we include all individual characteristics in the same regression. Similar results are obtained if we also include eye-gaze test and CRT scores.

is unlikely to capture this complex phenomenon, it is not surprising that extraversion performs relatively better than other skills when controlling for market observables. We state our first result as follows.

Result 1 (Individual Skills & Forecasting Performance)
Theory of mind (HS), standard cognitive skills, and extraversion significantly explain forecasting performance.

Next, we test Hypothesis 1i by assessing the conditions under which theory of mind skills predict forecasting performance. In Table 5, we assess the predictive power of theory of mind skills (HS) across markets varying in their level of mispricing, as measured by MAD. In regression (1) [(2)], we consider the markets for which the MAD value was below [above] the median value of all markets. In line with Hypothesis 1i, we show that theory of mind skills matter most when mispricing is low. Indeed, the coefficient for "HS score (std) × MAD" in regression (3) is positive and significant so that more mispricing induces higher forecasting errors for people who earned higher scores on the HS test. Similar findings are obtained using weight forecasting accuracy as the dependent variable (see Table C14 in Appendix C) and when adding individual and market controls to the regression analysis (see Tables C15 and C16 in Appendix C). The results in regression (3) of Table 5 also hold when using the interaction variable "HS score (std) × MAD Dummy", where MAD Dummy takes value one if the MAD of the market is above the median MAD of all markets (see Table C21). We should also note that, in line with Result 1 showing a limited predictive power of the eye-gaze test on forecasting performance, the findings of Table 5 do not hold in that case (see p-value = 0.336 in Table C17 in Appendix C for "Eye-gaze score (std) × MAD"). It is interesting to note that the behavioral experiment in BQB (n = 43) seems to indicate a possibly stronger relationship between theory of mind scores and forecasting performance for HS than for the eye-gaze test (see Figures 4 and 5 in BQB). In addition, BQB posit that the close connection between pattern recognition skills and theory of mind is crucial to understanding why theory of mind skills predict forecasting performance in markets. Because HS is a more direct measure of people's inherent inclination for pattern recognition than the eye-gaze test, that HS fares better might not be that unsurprising.[30]

[30] In line with our findings (see Table 2), BQB, do not find a significant correlation between performance on the eye-gaze and HS tests.

Table 5. Price forecasting error as predicted by theory of mind (HS) skills and mispricing

SAMPLE VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs
HS score (std)	**-4.11***** **(1.38)**	**-0.46** **(1.84)**	**-5.27***** **(1.44)**
HS score (std) × MAD			**0.03**** **(0.01)**
MAD			0.78*** (0.01)
Male Dummy	-4.71 (3.10)	-4.87 (3.92)	-4.82** (2.40)
Book Dummy	-2.12 (4.56)	-1.42 (4.51)	-1.73 (3.19)
Dynamics Dummy	3.08 (4.16)	-3.45 (4.76)	-0.32 (2.68)
Book & Dynamics Dummy	4.82 (5.94)	10.77 (6.67)	8.18* (4.30)
Two Insiders Dummy	22.11*** (2.76)	-2.22 (2.61)	7.69*** (1.87)
Six Insiders Dummy	-10.80*** (2.72)	-101.49*** (3.67)	-20.84*** (2.24)
Asset Value	-0.04*** (0.01)	0.04*** (0.01)	-0.03*** (0.01)
Constant	42.20*** (8.37)	213.68*** (9.33)	35.11*** (6.68)
Observations	3,746	3,748	7,494
R-squared	0.077	0.176	0.543
Chi-squared	485.7	2,287	14,818

Robust standard errors in parentheses with session and time fixed effects included as well as random effects for each subject. (std) indicates a standardized variable. *** p<0.01, ** p<0.05, * p<0.1.

To test Hypothesis 1ii, we replicate Table 5 for cases in which the graphical display available to forecasters is either complete (i.e., the book is displayed along with dynamic charts) or not (i.e., either the book or the dynamic charts are not displayed). We find supporting evidence for Hypothesis 1ii because the interaction effect between mispricing and HS scores appears to be moderated by the extent of the graphical display available to forecasters. Indeed, the interaction coefficient "HS score (std) × MAD" in regressions (5) and (6) in Table 6 is only significant and positive when the complete display is provided suggesting that it helps individuals with high theory of mind skills to predict the true asset value when mispricing is low (see "HS score (std)" in regression (1)) whereas it hurts forecasting performance for those with high theory of mind when mispricing is high (see "HS score (std)" in regression (3)). In the absence of a complete display, HS scores impact forecasting errors negatively (see regressions (2) and (4)).

Table 6. Price forecasting error as predicted by theory of mind skills, mispricing and graphical display

SAMPLE VARIABLES	(1) Below Median MAD & Complete Display	(2) Below Median MAD & Non-complete Display	(3) Above Median MAD & Complete Display	(4) Above Median MAD & Non-complete Display	(5) All MADs & Complete Display	(6) All MADs & Non-complete Display
HS score (std)	**-5.90**** **(2.76)**	**-4.11**** **(1.61)**	**6.51**** **(3.14)**	**-2.65** **(1.95)**	**-7.62***** **(2.44)**	**-5.15***** **(1.71)**
HS score (std) × MAD					**0.07***** **(0.02)**	**0.02** **(0.01)**
MAD					0.77*** (0.03)	0.78*** (0.02)
Male Dummy	8.78* (5.20)	-9.12** (3.70)	-1.73 (5.50)	-7.16 (4.66)	4.05 (4.47)	-8.08*** (2.71)
Book Dummy		-2.31 (4.61)		-1.57 (4.37)		-1.98 (3.12)
Dynamics Dummy		2.91 (4.07)		-3.36 (4.79)		-0.35 (2.71)
Two Insiders Dummy	22.60*** (5.88)	21.60*** (3.16)	-8.62 (5.74)	-0.30 (2.95)	5.05 (3.53)	8.44*** (2.21)
Six Insiders Dummy	-7.64 (5.58)	-12.42*** (3.09)	-111.18*** (5.28)	-99.04*** (4.38)	-23.70*** (4.60)	-20.33*** (2.55)
Asset Value	-0.05* (0.03)	-0.04*** (0.01)	0.06*** (0.02)	0.03*** (0.01)	-0.01 (0.02)	-0.03*** (0.01)
Constant	48.43*** (17.83)	40.44*** (9.42)	217.16*** (14.28)	215.38*** (10.72)	37.73*** (11.57)	36.22*** (7.59)
Observations	960	2,786	960	2,788	1,920	5,574
R-squared	0.141	0.0802	0.274	0.172	0.571	0.541

Robust standard errors in parentheses with session and time fixed effects included as well as random effects for each subject. (std) indicates a standardized variable. *** p<0.01, ** p<0.05, * p<0.1.

We verify the robustness of the results in Table 6 by using the weight forecasting accuracy (see Table C18 in Appendix C) as the dependent variable, and by adding individual and market controls (see Tables C19 and C20). When the weight forecasting accuracy is the dependent variable, "HS score (std) × MAD" has a similar implication to that shown in Table 6, but is only marginally significant (regression (5) in Table C18).[31] The main finding that graphical display plays a role in moderating the effect of theory of mind skills (HS) on forecasting performance continues to hold if we distinguish between dynamic and static displays instead of between complete and non-complete displays (see Table C22). This distinction is relevant for testing Hypothesis 1ii according to which pattern recognition skills, as measured with HS, will be especially crucial in explaining forecasting performance when the display prompts the identification of graphical patterns in the data. As was the case for Table 5, the results in Table 6 do not hold for the eye-gaze test (see Table C23). The reason the coefficient for "Eye-gaze score (std) × MAD" does not depend on the graphical display could be because the Eye-gaze test does not measure pattern recognition skills in the way the HS test does. We summarize our findings with respect to the mechanisms underlying the relationship between theory of mind skills and forecasting performance as our second result.

Result 2 (Theory of Mind, Mispricing, Graphical Display & Forecasting Performance)
i) Theory of mind skills (HS) enhance forecasting performance when mispricing is low.
ii) Theory of mind skills (HS) hurt forecasting performance when mispricing is high and the graphical display is complete.

To test Hypotheses 2 & 3, we replicate Table 5 for the case of standard cognitive skills and extraversion. In Table 7, we show that standard cognitive skills (intelligence tests scores) predict forecasting performance significantly when mispricing is low (see "Intelligence score (std)" in regression (1)) whereas this is not the case when mispricing is high (see regression (2)). Unlike theory of mind skills and in line with Hypothesis 2, intelligence scores do not hurt forecasting when mispricing is high. In addition, the interaction effect

[31] The results in Table 5 also hold when using the interaction variable "HS score (std) $\times$ MAD Dummy", where MAD Dummy takes value one if the MAD of the market is above the median MAD of all markets (see Table C21).

"Intelligence score (std) × MAD" in regression (3) fails to reach statistical significance (p-value = 0.199).

Table 7. Price forecasting error as predicted by standard cognitive skills and mispricing

SAMPLE	(1)	(2)	(3)
	Below Median	Above Median	All
VARIABLES	MAD	MAD	MADs
Intelligence score (std)	**-3.17****	**-1.21**	**-3.99****
	(1.45)	**(1.64)**	**(1.83)**
Intelligence score (std) × MAD			**0.01**
			(0.01)
MAD			0.78***
			(0.01)
Male Dummy	-4.54	-5.03	-4.86**
	(3.01)	(4.03)	(2.33)
Book Dummy	-2.11	-1.57	-1.83
	(4.61)	(4.51)	(3.27)
Dynamics Dummy	3.19	-3.42	-0.25
	(4.29)	(4.76)	(2.72)
Book & Dynamics Dummy	6.15	11.22*	9.11**
	(5.94)	(6.71)	(4.31)
Two Insiders Dummy	22.12***	-2.22	7.69***
	(2.76)	(2.61)	(1.87)
Six Insiders Dummy	-10.78***	-101.50***	-20.84***
	(2.72)	(3.67)	(2.24)
Asset Value	-0.04***	0.04***	-0.03***
	(0.01)	(0.01)	(0.01)
Constant	39.81***	213.23***	34.20***
	(8.16)	(9.34)	(6.56)
Observations	3,746	3,748	7,494
R-squared	0.0751	0.177	0.543
Chi-squared	517.8	2354	15783

Robust standard errors in parentheses with session and time fixed effects included as well as random effects for each subject. (std) indicates a standardized variable. *** p<0.01, ** p<0.05, * p<0.1.

We verify the robustness of the results in Table 7 by using the weight forecasting accuracy (see Table C24 in Appendix C) as the dependent variable, and by adding individual and market controls (see Tables C25 and C26).[32] We also repeat the same analysis for CRT scores as we did for intelligence scores in Table 6 (see Table C28). We also find cognitive reflection tends to be a significant predictor of forecasting performance when mispricing is low but not when it is high.[33] We summarize our findings regarding the relationship between mispricing, standard cognitive skills, and forecasting performance in Result 3.

Result 3 (Standard Cognitive Skills, Mispricing & Forecasting Performance)
Standard cognitive skills enhance forecasting performance when mispricing is low but not when it is high.

In Table 8, we show that in line with Hypothesis 3 and unlike theory of mind and standard cognitive skills, extraversion predicts forecasting performance significantly when mispricing is high (see "Extraversion (std)" in regression (2)) but not when mispricing is low (see regression (1)). However, the interaction effect "Extraversion (std) × MAD" in regression (3) fails to reach statistical significance (p-value = 0.513).

[32] These results also hold when using the interaction variable "Intelligence score (std) × MAD Dummy", where MAD Dummy takes value one if the MAD of the market is above the median MAD of all markets (see regression (1) in Table C27).

[33] Unlike the case of intelligence scores, the coefficient for "CRT score (std) × MAD" in regression (3) in Table C28 is positive and significant. However, this might be explained by the positive correlation between CRT and HS (see Table 2, $\rho = 0.248$). Regression (4) in Table C28 shows that the variable "CRT score (std) × MAD" loses statistical significance when controlling for HS scores and the interaction term "HS score (std) × MAD".

Table 8. Price forecasting error as predicted by extraversion and mispricing

SAMPLE VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs
Extraversion (std)	**-0.56**	**-3.83****	**-1.40**
	(1.41)	**(1.63)**	**(1.69)**
Extraversion (std) × MAD			**-0.01**
			(0.01)
MAD			0.78***
			(0.01)
Male Dummy	-3.81	-4.27	-4.07*
	(3.17)	(3.77)	(2.31)
Book Dummy	-1.56	-1.33	-1.41
	(4.70)	(4.47)	(3.28)
Dynamics Dummy	3.03	-4.15	-0.71
	(4.29)	(4.59)	(2.71)
Book & Dynamics Dummy	4.94	10.26	7.96*
	(6.13)	(6.49)	(4.28)
Two Insiders Dummy	22.12***	-2.21	7.69***
	(2.76)	(2.61)	(1.87)
Six Insiders Dummy	-10.78***	-101.48***	-20.84***
	(2.72)	(3.66)	(2.24)
Asset Value	-0.04***	0.04***	-0.03***
	(0.01)	(0.01)	(0.01)
Constant	39.47***	213.34***	33.94***
	(8.26)	(9.31)	(6.59)
Observations	3,746	3,748	7,494
R-squared	0.0731	0.178	0.543
Chi-squared	467.4	2295	14674

Robust standard errors in parentheses with session and time fixed effects included as well as random effects for each subject. (std) indicates a standardized variable. *** p<0.01, ** p<0.05, * p<0.1.

We check the robustness of the results in Table 8 by using the weight forecasting accuracy (see Table C29 in Appendix C) as the dependent variable, and by adding individual and market controls (see Tables C30 and C31).[34] Unlike all our previous findings, the weight

[34] Results also hold when using the interaction variable "Extraversion (std) × MAD Dummy", where MAD Dummy takes value one if the MAD of a market is above the median of all markets (regression (2) in Table C27).

forecasting accuracy results differ from the price forecasting error results. This is surprising given that the correlation between the two dependent variables (price forecasting error and weight forecasting accuracy) is particularly high (ρ = 0.848). Together, Tables 7 and C29 show that, although forecasters with high levels of extraversion produce lower forecasting errors when mispricing is high, they are not more likely to identify the true state in that case. This divergence is in line with the argument that extrovert forecasters tend to downplay market prices as reliable signals of traders' information. Instead, such forecasters might assume prices result from manipulative attempts or unsophisticated behavior. As a result, a high level of extraversion would lead forecasters to expect that the actual state is the one which is a priori most likely (i.e., 240). Acting on these beliefs would reduce price forecasting errors as compared to a strategy that places greater weight on either of the two extreme states (i.e., 50 or 490) when mispricing is high. However, it would not increase the likelihood of extrovert forecasters placing the most weight on the actual state as they would tend to systematically assign a high weight to state 240. Indeed, those whose level of extraversion is above the median place more weight on 240 than do those whose level of extraversion is below the median when mispricing is high (p-value = 0.004, Wilcoxon Rank Sum Test). The opposite is true for theory of mind skills as those with higher theory of mind skills, i.e., individuals who are supposedly more likely to follow price trends when mispricing is high, place less weight on 240 than those with lower theory of mind skills (using HS, p-value = 0.073 for Wilcoxon Rank Sum Test). We summarize our findings regarding the relationship between mispricing, extraversion and forecasting performance in Result 4.

Result 4 (Extraversion, Mispricing & Forecasting Performance)
Extraversion reduces forecasting errors when mispricing is high but not when it is low.

As an additional analysis, we show that there are no differences in the predictive power of individual skills between the two information structures that exhibit similar levels of mispricing (12-*partially informed* and 2-*fully informed* markets). The non-significant interaction coefficients between individual skills and the "Two Insiders Dummy" in Table C32 in Appendix C verify this pattern. This confirms that mispricing, and not the information structure of markets, is the key determinant for identifying the individual skills that best explain forecasting performance.

Finally, in Appendix D we report regression analyses showing no robust predictive power of individual characteristics for the proportion of traders possessing high CRT skills in a market. Regarding the prediction of the distribution of private information in the market, HS skills are found to significantly increase information structure forecasting accuracy whereas extraversion seems to decrease information structure forecasting accuracy. The success of HS is driven by predictions for the 6-*fully informed* markets (see Table D3), which also happens to be the information structure that forecasters are most likely to predict correctly (see "Six Insiders Dummy" in Table D2). In 6-*fully informed* markets, extrovert forecasters seem to fail to recognize that many traders are placing orders based on their private information. Extrovert traders also seem to have difficulty identifying those markets in which all traders possess imprecise private signals (i.e., 12-*partially informed* markets) (see regression (3) in Table D3). In fact, forecasters with high levels of extraversion are more likely to perceive 12-*partially informed* markets as being 2-*fully informed* markets as compared to those with low levels of extraversion (see regression (4) in Table D3).

5. Discussion

This paper reports the results of an experiment in which participants observe asset markets from prior experiments and forecast the underlying fundamental value of the asset being traded. In addition to the forecasting task, we use standard tests to measure the cognitive, emotional and social skills of the forecasters.

To the best of our knowledge, this is the first study jointly assessing the predictive power of theory of mind, standard cognitive skills, and personality traits on forecasting performance. Our behavioral results identify that specific forecasting skills exist and thus, success is not simply luck. In addition, our research design lays out and tests precise mechanisms by which each set of skills operates. This allows us to shed light on previous results in the literature such as the apparent contradictory effect of theory of mind skills in different market contexts.

Consistent with our hypotheses, we find the following three patterns. First, theory of mind skills are beneficial when mispricing is low in the market, but harmful when mispricing is high. Shedding light on the underlying mechanisms explaining these results, we show that these effects prevail when forecasters have access to a rich graphical display because it supposedly prompts high theory of mind individuals to search for patterns in the data. In cases in which market prices reflect private information (as in BQB or Corgnet, DeSantis and Porter, 2018), pattern recognition techniques will be beneficial whereas the opposite is true if prices are uninformative (as in De Martino et al. 2013, Hefti, Heinke and Schneider, 2018). Second, standard cognitive skills, such as fluid intelligence and cognitive reflection, are also beneficial when mispricing is low, but do not hurt forecasting performance when mispricing is high. This finding is new to the literature because a limited amount of data was available to date for assessing such conjecture. Third, the pattern found for extraversion is the opposite of that found for cognitive skills – a high degree of extraversion is associated with better forecasting when mispricing is high, but not when mispricing is low. This suggests extraversion helps forecasters disregard possibly misleading manipulation. This finding is also new to the literature.

Even though our results are encouraging, more research is needed in this area to identify other features of the environment that could impact the relationship between individual skills and forecasting performance. We hope that this paper helps to spark that effort. The fact that the main forecasting skills (theory of mind, fluid intelligence, and extraversion) are virtually uncorrelated suggests heterogeneous teams could perform especially well in forecasting tasks. This is perhaps one of the secrets of the wisdom of the crowd.

6. References

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7. Appendices

Appendix A. Analysis of Lo, Repin and Steenbarger, 2005 and Durand, Newby and Sanghani, 2008

We use the data in Lo, Repin and Steenbarger (2005) (80 investors) and Durand, Newby and Sanghani (2008) (21 investors) to show that investors score higher on the extraversion trait of personality compared to the broader adult or students populations. Both studies use the short version (120 items) Big-five personality test originally developed by McCrae and Costa (1992). We compare investors' scores with scores from broad set of adults who took the same tests (Ypofanti et al. 2015, *n* = 520) as well as two samples of students (Lim and Ployhart, 2006, *n* = 353 (Student I in Table A1); Donnellan et al. 2006, *n* = 2,663 (Student II in Table A1)). As is shown in Table A1 below, the findings suggest that investors exhibit a level of extraversion which is systematically higher than the adults and students samples.

Table A1. P-values (t-test) for comparisons of personality traits across different samples (in bold, significance at the 1% level)

Investors	Lo, Repin and Steenbarger (2005)			Durand, Newby and Sanghani (2008)		
SAMPLE comparisons	Investors vs Adults	Investors vs Students I	Investors vs Students II	Investors vs Adults	Investors vs Students I	Investors vs Students II
Extraversion	**<0.0001 (8.382)**	**<0.0001 (8.719)**	**<0.0001 (13.544)**	**0.0006 (3.470)**	**<0.0001 (4.697)**	**<0.0001 (4.476)**
Openness	**0.0010 (-3.318)**	0.2262 (-1.212)	0.0138 (-2.465)	0.9707 (-0.037)	0.0443 (-2.018)	0.0621 (-1.867)
Conscientiousness	**0.0003 (3.619)**	**<0.0001 (7.114)**	**<0.0001 (10.052)**	**<0.0001 (4.160)**	**<0.0001 (12.211)**	**<0.0001 (8.174)**
Agreeableness	**<0.0001 (-5.242)**	0.0124 (-2.511)	**<0.0001 (-5.716)**	0.0124 (-2.382)	0.7065 (-0.377)	0.9110 (-0.112)
Neuroticism	**0.0005 (3.505)**	0.0226 (2.289)	**<0.0001 (7.710)**	0.2665 (1.112)	0.0192 (2.352)	0.9103 (0.113)

Appendix B. Instructions and Example Screenshots

B.1. Instructions for Phase 2 of the experiment.

Hard copies of these instructions were distributed to the participants who were given approximately 5 minutes to read through each set (A.1.a and A.1.b). Participants kept the hard copy instructions with them throughout the experiment.

B.1.a

Introduction

This is an experiment in the economics of market decision making. You will be paid in cash at the end of the experiment based upon the decisions you make, so it is important that you understand the directions completely. If you have a question, please raise your hand and a monitor will approach you. Otherwise, you should not communicate in any way with anyone else.

Previous Experiments

You and everyone else who is in today's study has previously participated in one of several earlier studies in which you could buy and sell shares (or certificates) of an asset in a series of trading market periods. In those markets shares paid a dividend of either 50, 240 or 490 to the share's owner. The currency unit in the prior studies was either francs or experimental dollars (e-Dollars), but that is not important right now. The value of the dividend did not depend on who owned the share and in any period every share paid the same dividend.

In today's experiment you will be observing what happened in some of those trading periods from past experiments. Your task will be to accurately predict what the value of the dividend was in a trading period after observing what happened in the market that period. There will be more details later about today's task but first we will review how the trading market works to refresh everyone's memory and then we will have two practice trading periods.

Information

Before trading began in a market all 12 traders knew that assets can have a value of 50, 240 or 490. In each period there was a 35% chance the value would be 50, a 45% chance the value would be 240, and a 20% chance the value would be 490.

Before the market period began traders could receive clues about values the asset would *not* have.

In some experiments half of the traders were told one of the values the shares would not take that period while the other half of the traders were told the other value shares would not take that period. These traders are referred to as *partially informed*. So for example, if a share was worth 50 then six traders were informed the shares were not worth 240 and six were informed the shares are not worth 490.

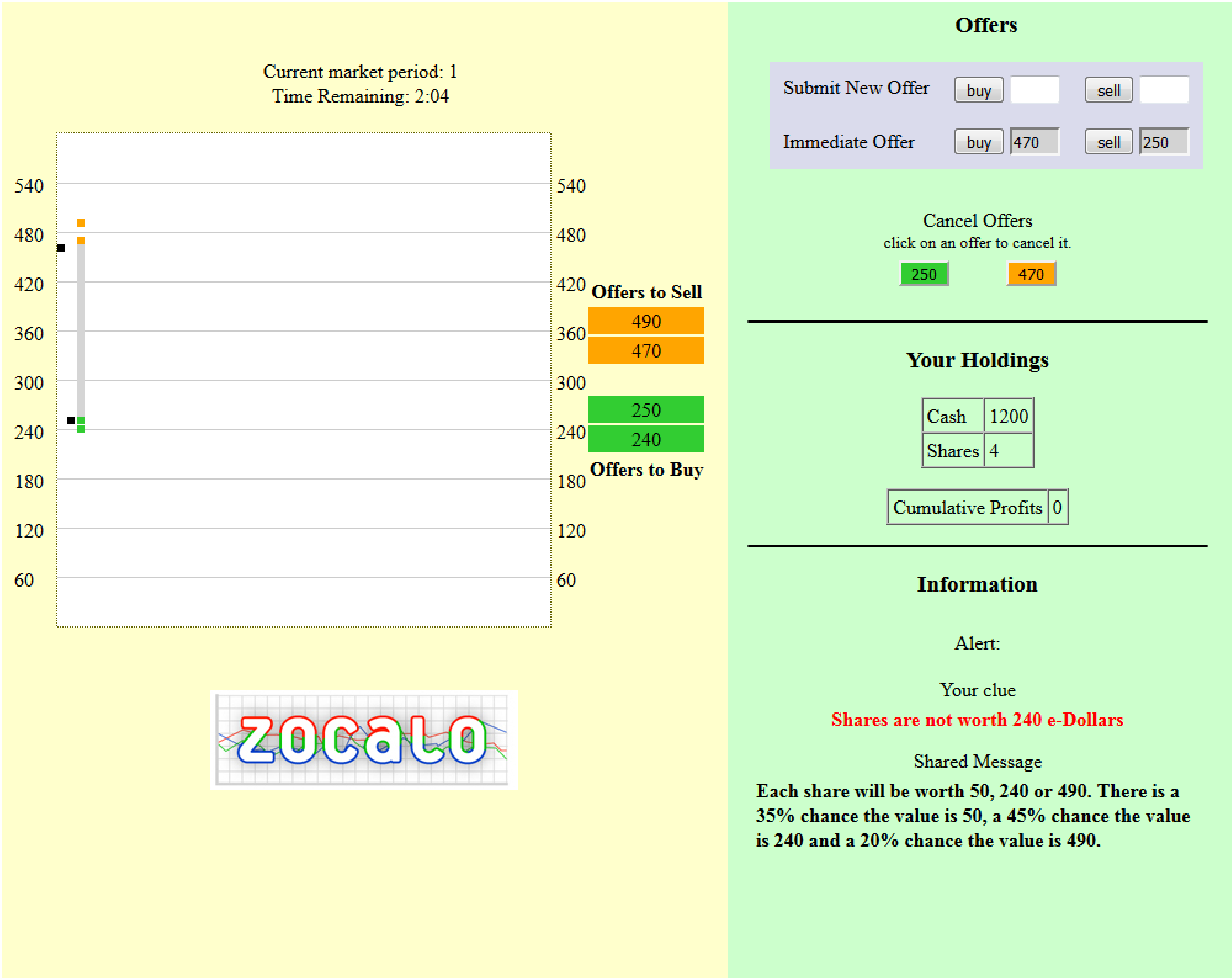
In other experiments some traders were given no information while others received two clues meaning these traders knew the value of the shares with certainty. For example, if the shares were worth 490 then some traders were informed that the shares were not worth 50 and not worth 240. These traders were referred to as *fully informed* traders. In some experiments half the traders were *fully informed* and in some experiments only two of the twelve traders were *fully informed*.

Market Graph

During every period, participants can buy or sell shares from one another by making offers to buy or to sell. The existing offers are shown on the Market Graph to the left.

Every time someone makes an offer to buy a share, a GREEN dot appears on the graph to the left. Every time someone makes an offer to sell, an ORANGE dot appears on the graph to the left. Once a trade is actually made, the trade will be shown as a BLACK dot in the graph.

Offers are also listed on the Offer Book to the right of the graph.



Current market period: 1
Time Remaining: 2:04
540
480
420
360
300
240
180
120
60
Offers to Sell
490
470
250
240
Offers to Buy
ZOCALO
Offers
Submit New Offer
buy
sell
Immediate Offer
buy
470
sell
250
Cancel Offers
click on an offer to cancel it.
250
470
Your Holdings
Cash
1200
Shares
4
Cumulative Profits
0
Information
Alert:
Your clue
Shares are not worth 240 e-Dollars
Shared Message
Each share will be worth 50, 240 or 490. There is a 35% chance the value is 50, a 45% chance the value is 240 and a 20% chance the value is 490.

Making and Accepting Offers

To accept an existing offer from another participant, click the Buy or Sell button in the **Immediate Offer** section of the screen. The Immediate Offer section shows you the best prices to buy, or sell, that are currently available in the market.

To place a new offer to buy or sell you enter it into the appropriate box beside **Submit New Offer** and then press the respective button. Any new offer to buy or sell must improve on the price that is currently shown in the immediate offer section.

You cannot place an offer to buy unless you have enough cash to pay that price. You cannot place an offer to sell a share you do not already own. Your current cash and shares are displayed under **Your Holdings**.

Practice Trading Periods

We will now go through two practice trading periods. This will not impact your payoff in any way, it is simply to refresh your memory with how the trading market works. In the first practice trading period every trader will be *partially informed*. In the second practice period some traders will be *fully informed*. After these practice periods are completed, you will not interact with any other participant during this study.

B.1.b

Forecasting Share Value

For 30 seconds you will observe what happened in an entire trading period that lasted several minutes during a previous experimental session. The graphs you are about to see have time on the x-axis rather than the trade number as in the practice markets you just completed. You will then be asked to state the chance you think the asset was worth 50, 240, and 490. Because the asset was worth one of these three values, your responses must sum to 100%.

Your payoff for this prediction is determined by a scoring rule. The formula is a little complicated, but what it means is that you maximize your expected payment by truthfully reporting your beliefs. The formula is:

$$\text{Your payoff} = 0.5\times[\,1 + (2) \times (\text{Chance you assigned to the actual true value}) - (\text{Chance you assigned to 50})^2 - (\text{Chance you assigned to 240})^2 - (\text{Chance you assigned to 490})^2\,].$$

Suppose the true asset value is 490. If you assign a chance of 20% for 50, 30% for 240, and 50% for 490, then your payoff for this prediction would be:

$$\text{Your payoff} = 0.5\times[1 + (2) \times (0.50)-(0.20)^2-(0.30)^2-(0.50)^2] = \$0.81.$$

If you correctly guess the true value of 490 by assigning a chance of 0% for 50, 0% for 240, and 100% for 490, then your payoff would be:

$$\text{Your payoff} = 0.5\times[1 + (2) \times (1)-(0)^2-(0)^2-(1)^2] = \$1.00,$$

which is the maximum payoff you can earn for a prediction. Again, although the formula is a bit complicated it is structured so that you maximize your expected payment by truthfully reporting your beliefs about the chances. Also note that your payoff cannot be negative.

Remember, that in each period there was a 35% chance the value would be 50, a 45% chance the value would be 240, and a 20% chance the value would be 490. But before trading began traders could receive more information about the value of shares that period.

Forecasting Trader Information

You will observe markets from several different experiments with different groups of traders. But you will be shown a block of five trading periods that are from the same experimental session. The trading periods you will see and the order in which they are shown to you is random. Which experiments are being shown was also chosen randomly.

After observing the block of five trading periods from a single session you will be asked to forecast how the information was structured in that experimental session. That is, we will ask you to state the chance that all traders were *partially informed* ('12 partially informed'), only two traders were *fully informed* ('2 fully informed, 10 uninformed'), and half the traders were *fully informed* ('6 fully informed, 6 uninformed') .

Your payment for this forecast uses the same scoring rule as the one for your forecast of the true value.

Forecasting Trader Survey Scores

Participants in these previous trading experiments were asked several questions in a survey. Some of those questions are listed below. They may look familiar since you were also asked these questions in the past.

(1) A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost?

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

(4) If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together?

(5) Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class?

(6) A man buys a pig for $60, sells it for $70, buys it back for $80, and sells it finally for $90. How much has he made?

(7) Simon decided to invest $8,000 in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Simon has: a. broken even in the stock market, b. is ahead of where he began, c. has lost money.

After observing the block of five trading periods from a single experimental session you will be asked to forecast how many of the participants in that session answered at least 4 of these questions correctly. That is, we will ask you to state the chance you think 0-3 people answered at least 4 questions correctly, 4-8 people answered at least 4 questions correctly, and 9-12 people answered at least 4 questions correctly.

Your payment for this forecast uses the same scoring rule as your other two forecasts.

B.1.c

Quiz

Please select the letter of the correct answer <u>on your computer screen</u>. Each correct answer is worth $0.50.

1. Which of the following statements regarding the share value is correct?

A. All values (50, 240 or 490) are equally likely.
B. 50 is more likely to occur than the other values.
C. 490 will occur on average 50% of the time.
D. 240 is more likely to occur than the other values.

2. You will observe several blocks of 5 trading market periods. Each period within a block of 5 trading market periods

A. Comes from the same previous experiment.
B. Comes from different previous experiments.
C. Has a different number of *partially informed* and/or *fully informed* traders.
D. Has a different number of participants who answered at least 4 of the survey questions correctly.

3. Choose the correct statement.

A. You will give the chance that the number of participants who answered at least 4 of the survey questions correctly is 0-3, 4-8, and 9-12 after <u>every</u> market period.

B. You will give the chance that the market period you observed came from a session where all traders were *partially informed* ('12 partially informed'), only two traders were *fully informed* ('2 fully informed, 10 uninformed'), and half the traders were *fully informed* ('6 fully informed, 6 uninformed') after <u>every</u> market period.

C. You will give the chance that the true asset value is 50, 240, or 490 after <u>every</u> market period.

Quiz Answers (to be read)

Please select the letter of the correct answer on your computer screen. Each correct answer is worth $0.50.

1. Which of the following statements regarding the share value is correct?

A. All values (50, 240 or 490) are equally likely.

B. 50 is more likely to occur than the other values.

C. 490 will occur on average 50% of the time.

D. 240 is more likely to occur than the other values.

Solution: The probabilities for values 50, 240, and 490 are 35%, 45%, and 20%, respectively. So, 240 is more likely to occur than the other values. So, **D** is the correct answer.

2. You will observe several blocks of 5 trading market periods. Each period within a block of 5 trading market periods

A. Comes from the same previous experiment.

B. Comes from different previous experiments.

C. Has a different number of *partially informed* and/or *fully informed* traders.

D. Has a different number of participants who answered at least 4 of the survey questions correctly.

Solution: Each period within a block of 5 trading market periods comes from the same previous experiment. So, each period has the same number of either *partially informed* or *fully informed* traders. And, each period has the same number of participants who answered at least 4 of the survey questions correctly. So, **A** is the correct answer.

3. Choose the correct statement.

A. You will give the chance that the number of participants who answered at least 4 of the survey questions correctly is 0-3, 4-8, and 9-12 after <u>every</u> market period.

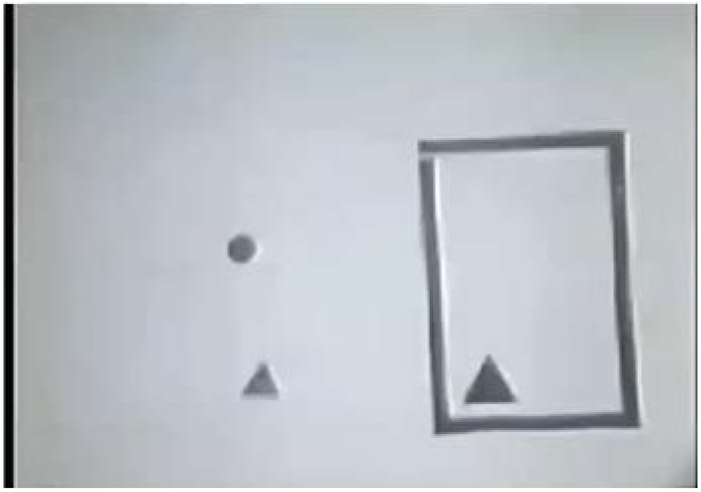
B. You will give the chance that the market period you observed came from a session where all traders were *partially informed* ('12 partially informed'), only two traders were *fully informed* ('2 fully informed, 10 uninformed'), and half the traders were *fully informed* ('6 fully informed, 6 uninformed') after <u>every</u> market period.

C. You will give the chance that the true asset value is 50, 240, or 490 after <u>every</u> market period.

Solution: You will give the chance that the true asset value is 50, 240, or 490 after every market period. As blocks of 5 trading market periods are from the same previous experiment, you will only give the chance that the number of participants who answered at least 4 of the survey questions correctly is 0-3, 4-8, and 9-12 after each block of 5 periods. Similarly, you will only give the chance that the market period you observed came from a session with 12 *partially informed* traders, 2 *fully informed* traders, or 6 *fully informed* traders after each block of 5 periods. So, **C** is the correct answer.

B.2. Instructions for Phase 3 of the experiment.

B.2.i. Heider-Simmel Test.



Movie: predict moves of large triangle

In this portion of the study, you will watch a movie of three geometric objects: a circle and two triangles, one small and the other one large. The objects move around, into, inside, and out of a box.

You are asked to predict the movement of the large triangle. The movie will be stopped after 5 seconds, at which point you will be given 10 seconds to choose whether, in 5 seconds, the large triangle is going to be *closer to* or *farther away from* the small triangle than at present. You indicate your choice by clicking on it.

After your choice, we play the movie for another 5 seconds, stop the movie again, and a message will be displayed to indicate whether you won (if your prediction was right), or whether you pay a penalty because you failed to make a decision within the allotted time. You will again be asked to predict the movement of the large triangle over the next 5 seconds of the video.

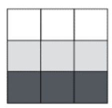
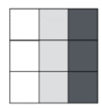
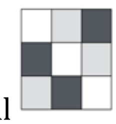
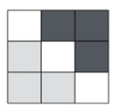
We then re-start the movie for 5 seconds and continue these cycles until the end of the movie.

You win $1 for every correct prediction. You pay a penalty of $0.25 for any failure to decide.

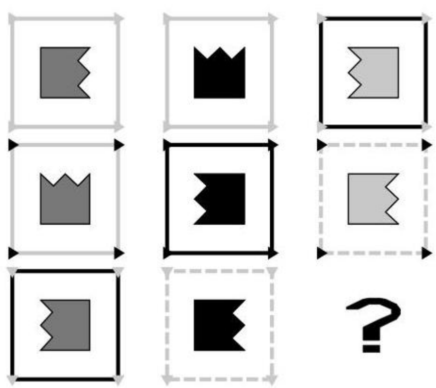
B.2.ii. Cognitive Ability Test

In this portion of the study, you will be given pattern problems to solve. For the following questions, you will be shown a 3 by 3 table of images with the image in the lower right missing. Please select the answer that best completes the pattern (i.e., the image that belongs in the lower right of the table).

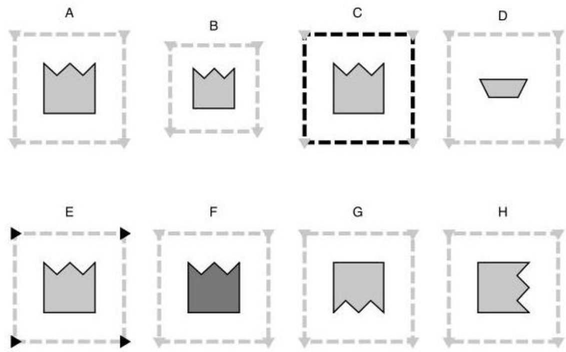
Images can vary according to their shape, size, color, direction, border style, and border corner marker. These image characteristics can change in the table in several ways:

They can change from row to row , by column , along the diagonal  or , and by the corner  or .

So the problems can be very, very difficult, like the example below. It is OK to guess.



In this example, the missing image should have a light gray dashed border, since this characteristic changes by the corner. The border markers should be downward pointing gray triangles since this characteristic changes by the row. The shape should be light gray because this changes by the column. The three pointed side of the shape should be facing up as the direction changes by the diagonal. Therefore, option “A” is the correct answer. Notice the shape and its size do not change.



You will have 6 minutes to answer the following 12 questions, and you will receive $0.50 for each correct answer.

B.2.iii. Cognitive Ability Test

In this portion of the study, you will see a square composed of 49 boxes. Behind one of these boxes hides a mine; all the other 48 boxes are free from mines. You do not know where this mine lies. You only know that the mine can be in any place with equal probability.

Your task is to choose how many boxes to collect. Boxes will be collected in order (left to right and then top to bottom). So you will be asked to choose a number between 1 and 49 of boxes to collect.

The location of the mine is random and will be revealed to you after you submit your decision.

If you happen to have selected the box where the mine is located, then you will earn zero. If the mine is located in a box that you did not select, then you will earn $0.10 per box you collected.

You will have 2 minutes to make your selection.

B.2.iv. Eye-gaze Test

In this portion of the study, you will view 10 sets of eyes. For each set of eyes, select which word best describes what the person in the picture is thinking or feeling. You may feel that more than one word is applicable but please choose just one word, the word which you consider to be most suitable. Before making your choice, make sure that you have read all 4 words. You should try to do the task as quickly as possible. You will have 6 minutes to make your selections. If you really don't know what a word means, during the task you can refer back to this Instructions tab which includes definitions of each word.

Please note that a listing of all words (adjectives) along with their definitions and use in a sentence was also provided as part of these instructions. Participants were able to freely switch between the task and this instruction set so that they could look up any words with which they were not familiar.

B.2.i. HEXACO

In this portion of the study, you will find a series of statements about you. Please read each statement and decide how much you agree or disagree with that statement. Then give your response using the following scale:

5 = strongly agree

4 = agree

3 = neutral (neither agree nor disagree)

2 = disagree

1 = strongly disagree

Please answer every statement, even if you are not completely sure of your response.

You will have 10 minutes to answer these questions.[35]

You will then complete a short demographic survey.

[35] The 60 personality questions are available here: https://hexaco.org/hexaco-inventory.

Figures B1 through B4 provide sample screenshots from the main forecasting task by treatment.

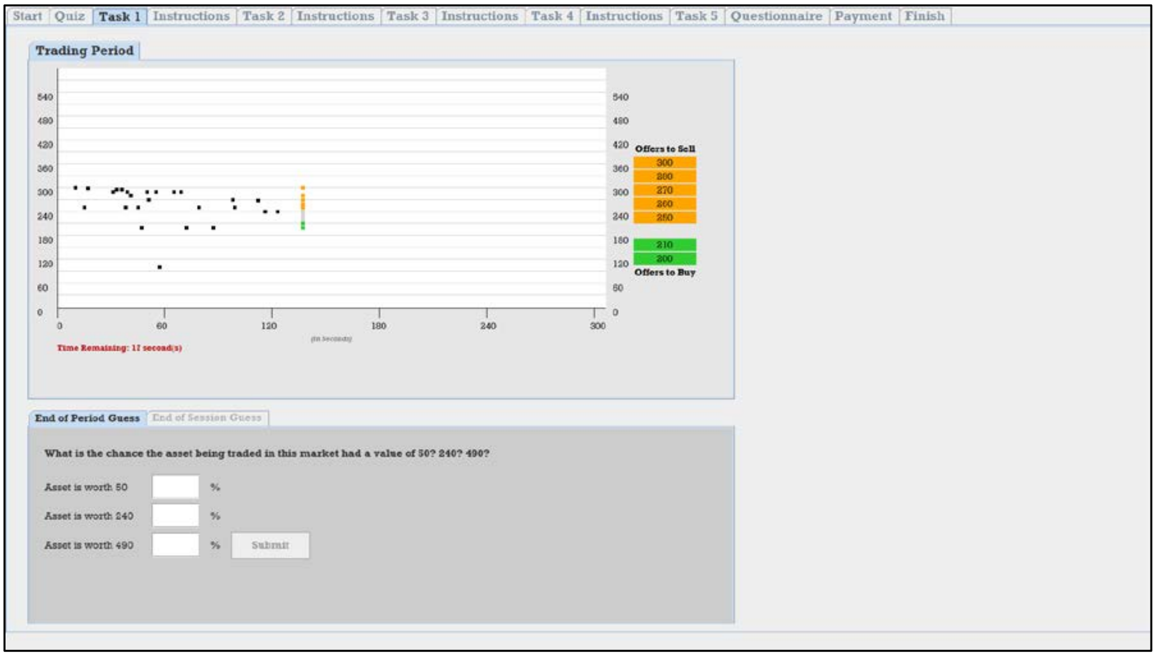


Figure B1. Dynamic – Book.

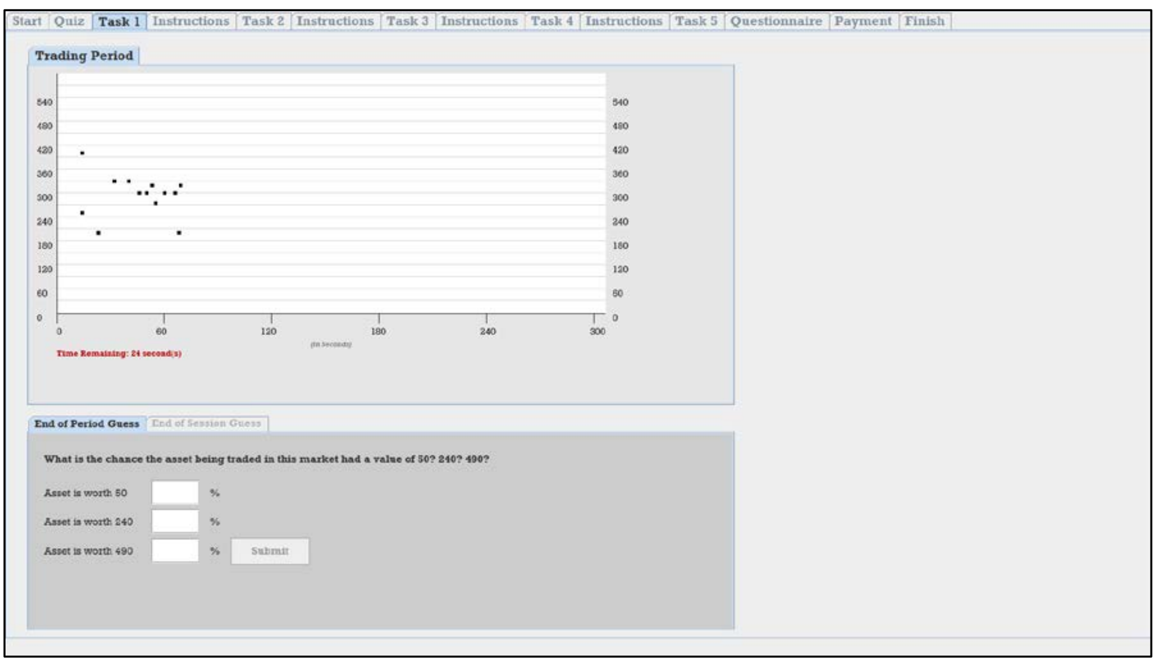


Figure B2. Dynamic – No Book.

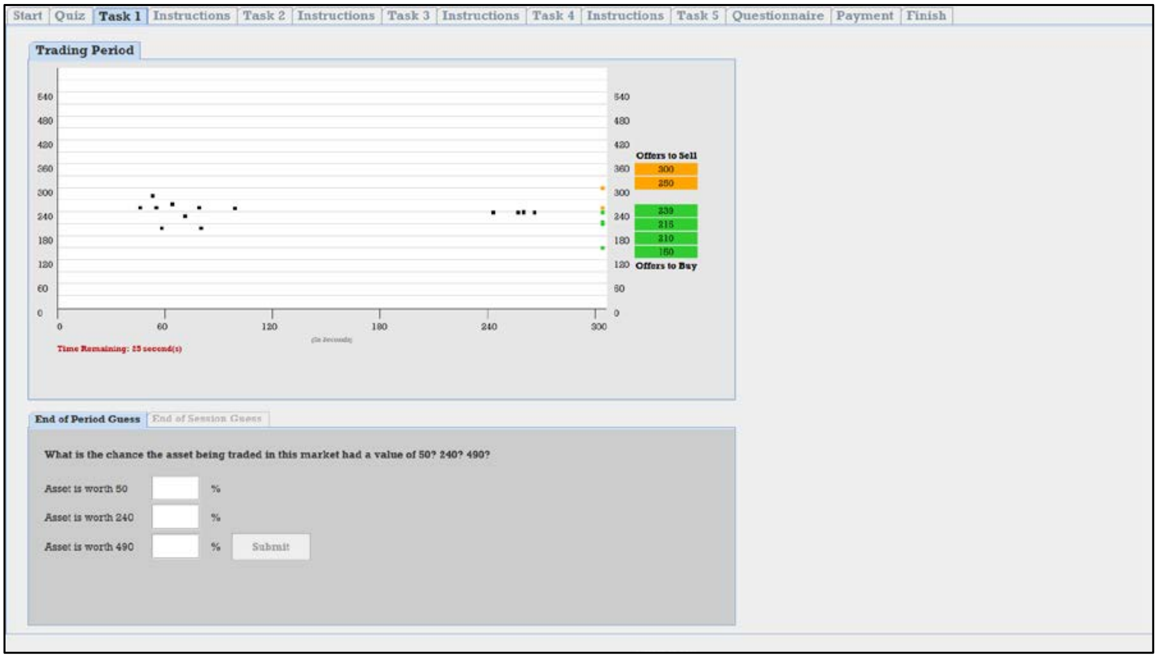


Figure B3. Static – Book.

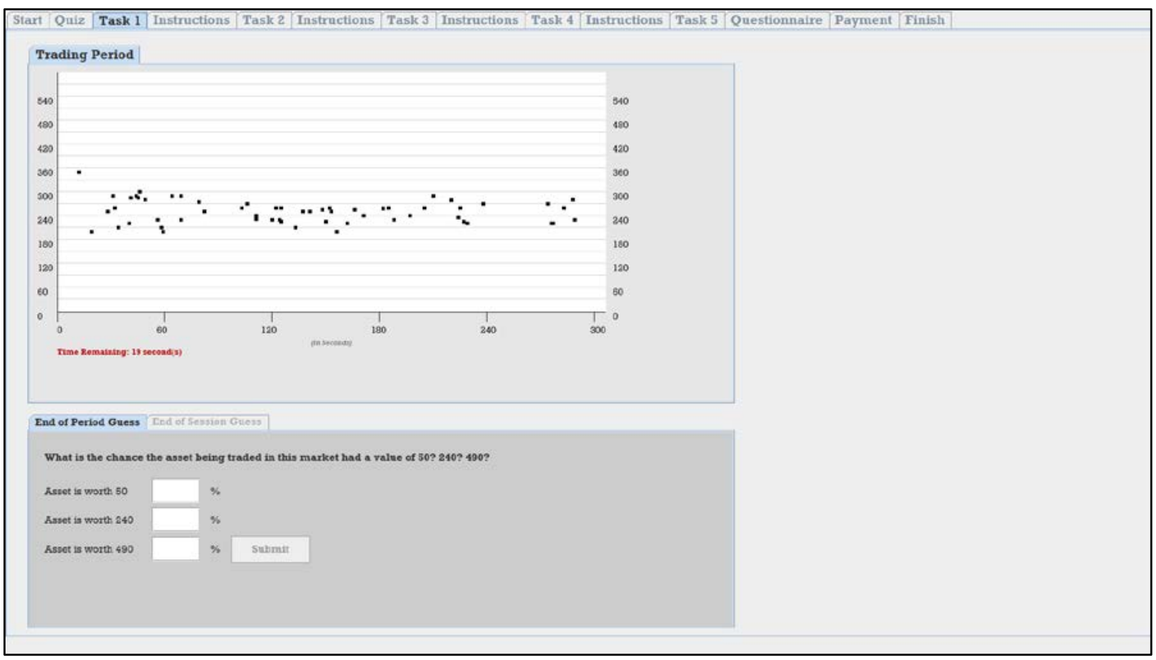


Figure B4. Static – No Book

Appendix C. Additional analyses

All linear panel regressions use robust standard errors in parentheses with session and time fixed effects as well as random effects for each subject. (std) indicates a standardized variable. We denote: *** p<0.01, ** p<0.05, * p<0.1

Table C1. Weight forecasting accuracy as predicted by individual characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)
Intelligence score (std)	**0.93***				
	(0.54)				
CRT score (std)		**0.57**			
		(0.43)			
HS score (std)			**1.10****		
			(0.49)		
Eye-gaze score (std)				**-0.11**	
				(0.52)	
Extraversion (std)					**0.99****
					(0.50)
Male Dummy	2.62**	2.35**	2.65**	2.43**	2.30**
	(1.08)	(1.08)	(1.08)	(1.08)	(1.05)
Book Dummy	0.72	0.80	0.71	0.61	0.55
	(1.52)	(1.54)	(1.49)	(1.56)	(1.53)
Dynamics Dummy	0.08	0.24	0.11	0.11	0.28
	(1.24)	(1.24)	(1.21)	(1.26)	(1.22)
Book & Dynamics Dummy	-3.32*	-3.35*	-2.93	-3.00	-2.85
	(1.98)	(1.96)	(1.97)	(1.99)	(1.96)
Two Insiders Dummy	-1.41**	-1.41**	-1.41**	-1.41**	-1.41**
	(0.66)	(0.66)	(0.66)	(0.66)	(0.66)
Six Insiders Dummy	31.34***	31.34***	31.34***	31.34***	31.34***
	(0.98)	(0.98)	(0.98)	(0.98)	(0.98)
Asset Value	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	42.75***	42.47***	41.98***	42.71***	42.76***
	(3.51)	(3.57)	(3.59)	(3.57)	(3.48)
Observations	7,494	7,494	7,494	7,494	7,494
R-squared	0.199	0.198	0.199	0.198	0.199
Chi-squared	2,315	2,352	2,335	2,443	2,371

Table C2. Price forecasting error as predicted by individual characteristics (all together)

VARIABLES	(1)	(2)	(3)
Intelligence score (std)	**-2.23****	**-2.19****	**-2.39****
	(1.11)	**(1.11)**	**(1.08)**
CRT score (std)	**-0.71**	**-0.64**	
	(1.01)	**(1.02)**	
HS score (std)	**-1.82**	**-1.84**	**-2.02***
	(1.16)	**(1.17)**	**(1.10)**
Eye-gaze score (std)	**0.64**		
	(1.19)		
Extraversion (std)	**-1.97***	**-2.04****	**-1.95***
	(1.03)	**(1.02)**	**(1.00)**
Male Dummy	-4.87**	-4.87**	-5.05**
	(2.35)	(2.35)	(2.29)
Book Dummy	-2.79	-2.45	-2.23
	(2.96)	(3.06)	(3.07)
Dynamics Dummy	-0.92	-0.81	-0.63
	(2.65)	(2.64)	(2.64)
Book & Dynamics Dummy	9.32**	9.15**	8.81**
	(4.19)	(4.24)	(4.21)
Two Insiders Dummy	15.02***	15.02***	15.02***
	(1.92)	(1.92)	(1.92)
Six Insiders Dummy	-87.80***	-87.80***	-87.80***
	(2.01)	(2.01)	(2.01)
Asset Value	0.12***	0.12***	0.12***
	(0.01)	(0.01)	(0.01)
Constant	106.25***	105.65***	105.41***
	(9.11)	(9.11)	(9.12)
Observations	7,494	7,494	7,494
R-squared	0.226	0.226	0.226
Chi-squared	6374	6361	6298

Table C3. Weight forecasting accuracy as predicted by individual characteristics (all together)

VARIABLES	(1)	(2)	(3)
Intelligence score (std)	**0.92***	**0.92***	**0.95***
	(0.53)	**(0.53)**	**(0.51)**
CRT score (std)	**0.12**	**0.11**	
	(0.44)	**(0.44)**	
HS score (std)	**0.99****	**0.99****	**1.03****
	(0.50)	**(0.50)**	**(0.48)**
Eye-gaze score (std)	**-0.07**		
	(0.49)		
Extraversion (std)	**0.86***	**0.87***	**0.85***
	(0.52)	**(0.52)**	**(0.52)**
Male Dummy	2.68**	2.68**	2.72***
	(1.07)	(1.07)	(1.05)
Book Dummy	0.94	0.90	0.86
	(1.40)	(1.42)	(1.42)
Dynamics Dummy	0.29	0.28	0.25
	(1.19)	(1.18)	(1.18)
Book & Dynamics Dummy	-3.24*	-3.22*	-3.16*
	(1.90)	(1.90)	(1.91)
Two Insiders Dummy	-1.41**	-1.41**	-1.41**
	(0.66)	(0.66)	(0.66)
Six Insiders Dummy	31.34***	31.34***	31.34***
	(0.98)	(0.98)	(0.98)
Asset Value	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)
Constant	41.81***	41.88***	41.92***
	(3.47)	(3.47)	(3.47)
Observations	7,494	7,494	7,494
R-squared	0.200	0.200	0.200
Chi-squared	2396	2316	2305

Table C4. Price forecasting error and weight forecasting accuracy as predicted by individual characteristics with additional controls[36]

VARIABLES	(1) Price Forecasting Error	(2) Weight Forecasting Accuracy
Intelligence score (std)	**-2.21****	**1.00***
	(1.07)	**(0.54)**
HS score (std)	**-1.94***	**1.02****
	(1.11)	**(0.46)**
Extraversion (std)	**-1.88***	**0.84**
	(1.10)	**(0.54)**
Male Dummy	-5.80**	2.51*
	(2.89)	(1.29)
Book Dummy	-3.24	1.18
	(3.14)	(1.46)
Dynamics Dummy	-3.04	1.35
	(2.85)	(1.28)
Book & Dynamics Dummy	11.18**	-4.28**
	(4.83)	(2.10)
Two Insiders Dummy	15.02***	-1.41**
	(1.93)	(0.66)
Six Insiders Dummy	-87.80***	31.34***
	(2.01)	(0.98)
Openness (std)	0.08	-0.18
	(1.14)	(0.53)
Conscientiousness (std)	0.79	-0.54
	(1.00)	(0.51)
Agreeableness (std)	0.05	-0.34
	(1.04)	(0.48)
Emotionality (std)	-0.92	-0.10
	(1.53)	(0.67)
Honesty (std)	1.72	-0.51
	(1.20)	(0.51)
Risk Taking score (std)	-0.07	-0.10

[36] We only include the individual characteristics which were significant predictors in Tables C2 and C3. Similar findings are obtained if we add eye-gaze and CRT scores to the analysis.

	(1.13)	(0.52)
Stock Participation Dummy[37]	3.07	-0.29
	(3.49)	(1.68)
Business School Dummy[38]	-2.86	0.35
	(3.13)	(1.30)
Humanities School Dummy[39]	1.05	-0.09
	(4.28)	(1.82)
Science School Dummy[40]	3.73	-2.47
	(4.30)	(1.83)
Asset Value	0.12***	-0.01***
	(0.01)	(0.00)
Constant	107.16***	41.91***
	(9.34)	(3.60)
Observations	7,494	7,494
R-squared	0.227	0.201
Chi-squared	6794	2824

[37] It takes value one for participants who answered 'yes' to the demographic question: "Do you regularly look at stock prices?".
[38] It takes value one for participants who stated they were affiliated to the Business school.
[39] It takes value one for participants who stated they were affiliated to the school of Humanities.
[40] It takes value one for participants who stated they were affiliated to the school of Science.

Table C5. Price forecasting error as predicted by individual median characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)
Intelligence Above Median Dummy	**-3.80***				
	(2.34)				
CRT Above Median Dummy		**-3.52***			
		(2.07)			
HS Above Median Dummy			**-4.33***		
			(2.28)		
Extraversion Above Median Dummy				**-3.35**	
				(2.16)	
Eye-gaze Above Median Dummy					**0.04**
					(2.29)
Male Dummy	-4.62**	-4.30*	-4.67*	-4.29*	-4.42*
	(2.34)	(2.40)	(2.39)	(2.36)	(2.40)
Book Dummy	-1.53	-2.26	-1.37	-1.79	-1.56
	(3.36)	(3.27)	(3.32)	(3.32)	(3.35)
Dynamics Dummy	-0.36	-0.88	-0.36	-0.93	-0.27
	(2.79)	(2.72)	(2.75)	(2.66)	(2.79)
Book & Dynamics Dummy	8.53*	9.58**	8.14*	8.56**	8.32*
	(4.36)	(4.29)	(4.32)	(4.30)	(4.39)
Two Insiders Dummy	15.01***	15.01***	15.01***	15.01***	15.01***
	(1.93)	(1.92)	(1.93)	(1.92)	(1.93)
Six Insiders Dummy	-87.81***	-87.81***	-87.81***	-87.81***	-87.81***
	(2.01)	(2.01)	(2.01)	(2.01)	(2.01)
Asset Value	0.12***	0.12***	0.12***	0.12***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	106.55***	106.54***	106.97***	105.62***	103.60***
	(9.06)	(9.25)	(9.46)	(9.20)	(9.31)
Observations	7,494	7,494	7,494	7,494	7,494
R-squared	0.225	0.225	0.226	0.225	0.225
Chi-squared	5995	6169	6230	6012	6108

Table C6. Weight forecasting accuracy as predicted by individual median characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)
Intelligence Above Median Dummy	**1.49**				
	(1.06)				
CRT Above Median Dummy		**1.59***			
		(0.92)			
HS Above Median Dummy			**1.63**		
			(1.02)		
Extraversion Above Median Dummy				**1.04**	
				(1.03)	
Eye-gaze Above Median Dummy					**0.71**
					(1.07)
Male Dummy	2.51**	2.37**	2.52**	2.39**	2.44**
	(1.07)	(1.07)	(1.08)	(1.07)	(1.08)
Book Dummy	0.55	0.88	0.49	0.63	0.46
	(1.56)	(1.52)	(1.55)	(1.56)	(1.56)
Dynamics Dummy	0.13	0.36	0.12	0.30	0.18
	(1.26)	(1.23)	(1.24)	(1.22)	(1.24)
Book & Dynamics Dummy	-3.07	-3.55*	-2.92	-3.06	-3.02
	(1.99)	(1.95)	(1.98)	(1.99)	(1.99)
Two Insiders Dummy	-1.41**	-1.41**	-1.41**	-1.41**	-1.41**
	(0.66)	(0.66)	(0.66)	(0.66)	(0.66)
Six Insiders Dummy	31.34***	31.34***	31.34***	31.34***	31.34***
	(0.98)	(0.98)	(0.98)	(0.98)	(0.98)
Asset Value	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	41.66***	41.49***	41.54***	42.19***	42.53***
	(3.55)	(3.60)	(3.72)	(3.55)	(3.63)
Observations	7,494	7,494	7,494	7,494	7,494
R-squared	0.198	0.198	0.198	0.198	0.198
Chi-squared	2320	2361	2342	2335	2407

Table C7. Price forecasting error as predicted by individual median characteristics (all together)

VARIABLES	(1)	(2)
Intelligence Above Median Dummy	**-4.10***	**-4.54****
	(2.26)	**(2.25)**
CRT Above Median Dummy	**-2.33**	
	(2.08)	
HS Above Median Dummy	**-4.41***	**-4.59***
	(2.33)	**(2.38)**
Extraversion Above Median Dummy	**-2.29**	**-2.48**
	(2.28)	**(2.25)**
Eye-gaze Above Median Dummy	**0.24**	
	(2.26)	
Male Dummy	-4.72**	-4.83**
	(2.30)	(2.30)
Book Dummy	-2.01	-1.51
	(3.09)	(3.23)
Dynamics Dummy	-1.28	-0.96
	(2.63)	(2.70)
Book & Dynamics Dummy	9.35**	8.56**
	(4.15)	(4.26)
Two Insiders Dummy	15.02***	15.02***
	(1.92)	(1.92)
Six Insiders Dummy	-87.80***	-87.80***
	(2.01)	(2.01)
Asset Value	0.12***	0.12***
	(0.01)	(0.01)
Constant	113.42***	112.17***
	(9.36)	(9.29)
Observations	7,494	7,494
R-squared	0.226	0.226
Chi-squared	6187	6021

Table C8. Weight forecasting accuracy as predicted by individual median characteristics (all together)

VARIABLES	(1)	(2)
Intelligence Above Median Dummy	**1.78***	**1.56**
	(1.03)	**(1.03)**
CRT Above Median Dummy		**1.10**
		(0.94)
HS Above Median Dummy	**1.78***	**1.68**
	(1.05)	**(1.03)**
Extraversion Above Median Dummy	**0.70**	**0.65**
	(1.06)	**(1.06)**
Eye-gaze Above Median Dummy		**0.61**
		(1.05)
Male Dummy	2.60**	2.56**
	(1.06)	(1.05)
Book Dummy	0.52	0.66
	(1.53)	(1.48)
Dynamics Dummy	0.31	0.55
	(1.23)	(1.19)
Book & Dynamics Dummy	-3.06	-3.47*
	(1.97)	(1.89)
Two Insiders Dummy	-1.41**	-1.41**
	(0.66)	(0.66)
Six Insiders Dummy	31.34***	31.34***
	(0.98)	(0.98)
Asset Value	-0.01***	-0.01***
	(0.00)	(0.00)
Constant	39.63***	38.75***
	(3.65)	(3.67)
Observations	7,494	7,494
R-squared	0.199	0.199
Chi-squared	2297	2472

Table C9. Price forecasting error as predicted by individual quartile characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)
Intelligence Top Quartile Dummy	**-8.72****				
	(3.57)				
CRT Top Quartile Dummy		**-5.23***			
		(2.72)			
HS Above Median Dummy			**-4.33***		
			(2.28)		
Eye-gaze top Quartile Dummy				**2.91**	
				(2.86)	
Extraversion Top Quartile Dummy					**-7.91*****
					(2.66)
Male Dummy	3.78	1.60	-4.67*	-2.90	-10.39***
	(3.56)	(2.80)	(2.39)	(2.98)	(3.01)
Book Dummy	-6.29	-1.85	-1.37	0.69	-6.61*
	(5.53)	(4.17)	(3.32)	(4.70)	(3.41)
Dynamics Dummy	-5.08	1.14	-0.36	-3.25	-0.44
	(5.09)	(3.82)	(2.75)	(3.67)	(3.22)
Book & Dynamics Dummy	14.45**	7.49	8.14*	6.16	13.23***
	(7.03)	(5.74)	(4.32)	(5.91)	(4.61)
Two Insiders Dummy	15.42***	14.67***	15.01***	15.57***	15.15***
	(3.41)	(2.99)	(1.93)	(2.32)	(2.74)
Six Insiders Dummy	-88.01***	-90.16***	-87.81***	-86.48***	-84.70***
	(3.28)	(2.70)	(2.01)	(2.58)	(3.10)
Asset Value	0.13***	0.12***	0.12***	0.12***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	110.11***	111.55***	106.97***	113.89***	105.00***
	(13.19)	(12.86)	(9.46)	(12.58)	(12.30)
Observations	3,058	3,960	7,494	4,618	3,714
R-squared	0.242	0.240	0.226	0.219	0.223

Table C10. Weight forecasting accuracy as predicted by individual quartile characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)
Intelligence Top Quartile Dummy	**3.39****				
	(1.70)				
CRT Top Quartile Dummy		**1.96***			
		(1.18)			
HS Top Quartile Dummy			**2.47****		
			(1.25)		
Eye-gaze top Quartile Dummy				**-1.02**	
				(1.27)	
Extraversion Top Quartile Dummy					**3.19****
					(1.41)
Male Dummy	-0.69	-0.08	2.28*	1.68	4.42***
	(1.59)	(1.20)	(1.37)	(1.31)	(1.57)
Book Dummy	4.80*	0.67	1.43	0.05	2.16
	(2.62)	(2.02)	(1.66)	(1.97)	(1.86)
Dynamics Dummy	4.43**	0.08	0.08	1.09	-0.49
	(2.17)	(1.72)	(1.59)	(1.54)	(1.55)
Book & Dynamics Dummy	-7.43**	-3.64	-3.10	-2.71	-4.78*
	(3.30)	(2.63)	(2.41)	(2.55)	(2.48)
Two Insiders Dummy	-1.01	-1.15	-1.48	-1.33*	-0.68
	(1.24)	(1.04)	(0.91)	(0.77)	(0.89)
Six Insiders Dummy	30.05***	31.70***	33.21***	31.34***	30.55***
	(1.68)	(1.36)	(1.22)	(1.26)	(1.49)
Asset Value	-0.01***	-0.01***	-0.02***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	41.56***	38.12***	43.30***	37.96***	42.23***
	(5.31)	(5.38)	(4.84)	(4.57)	(4.64)
Observations	3,058	3,960	4,556	4,618	3,714
R-squared	0.203	0.211	0.212	0.195	0.197

Table C11. Price forecasting error as predicted by individual quartile characteristics (all together)

VARIABLES	(1)	(2)
Intelligence Top Quartile Dummy	**-4.87***	**-5.08****
	(2.56)	**(2.39)**
CRT Top Quartile Dummy	**-0.59**	
	(2.30)	
HS Top Quartile Dummy	**-5.99*****	**-6.00*****
	(2.10)	**(2.11)**
Eye-gaze top Quartile Dummy	**0.70**	
	(2.42)	
Extraversion Top Quartile Dummy	**-4.50****	**-4.52****
	(2.29)	**(2.25)**
Male Dummy	-5.92**	-6.08**
	(2.43)	(2.39)
Book Dummy	-2.63	-2.55
	(2.95)	(2.97)
Dynamics Dummy	-0.72	-0.69
	(2.64)	(2.64)
Book & Dynamics Dummy	8.83**	8.78**
	(4.11)	(4.13)
Two Insiders Dummy	15.01***	15.01***
	(1.92)	(1.92)
Six Insiders Dummy	-87.80***	-87.81***
	(2.01)	(2.01)
Asset Value	0.12***	0.12***
	(0.01)	(0.01)
Constant	111.16***	111.27***
	(9.32)	(9.25)
Observations	7,494	7,494
R-squared	0.227	0.227
Chi-squared	6405	6370

Table C12. Weight forecasting accuracy as predicted by individual quartile characteristics (all together)

VARIABLES	(1)	(2)
Intelligence Top Quartile Dummy	**2.34***	**2.07***
	(1.32)	**(1.18)**
CRT Top Quartile Dummy	**-0.75**	
	(1.10)	
HS Top Quartile Dummy	**2.96*****	**2.97*****
	(0.95)	**(0.95)**
Eye-gaze top Quartile Dummy	**0.39**	
	(1.09)	
Extraversion Top Quartile Dummy	**1.81***	**1.84***
	(1.09)	**(1.09)**
Male Dummy	3.30***	3.16***
	(1.12)	(1.09)
Book Dummy	0.94	1.02
	(1.41)	(1.41)
Dynamics Dummy	0.27	0.30
	(1.23)	(1.22)
Book & Dynamics Dummy	-3.12*	-3.18*
	(1.88)	(1.89)
Two Insiders Dummy	-1.41**	-1.41**
	(0.66)	(0.66)
Six Insiders Dummy	31.34***	31.34***
	(0.98)	(0.98)
Asset Value	-0.01***	-0.01***
	(0.00)	(0.00)
Constant	39.34***	39.32***
	(3.58)	(3.52)
Observations	7,494	7,494
R-squared	0.201	0.201
Chi-squared	2692	2582

Table C13. Price forecasting error as predicted by individual characteristics with market controls

Amplitude of prices was calculated as the percentage difference between high and low prices in a given market. Average price was equal to the average transacted price in a market. Excess bids was calculated as the difference between the total number of bids and asks in a given market. Volume was the sum of all transactions in a market.

VARIABLES	(1) Price Forecasting Error	(2) Weight Forecasting Accuracy
Intelligence score (std)	**-2.13****	**0.82***
	(1.04)	**(0.49)**
HS score (std)	**-1.76***	**0.88***
	(1.04)	**(0.47)**
Extraversion (std)	**-2.20****	**0.97***
	(1.05)	**(0.55)**
Male Dummy	-4.82**	2.67**
	(2.34)	(1.07)
Mean Absolute Deviation (std)	75.28***	-17.53***
	(1.34)	(0.67)
Amplitude of prices (std)	2.31***	-2.13***
	(0.76)	(0.32)
Average Price (std)	9.18***	-2.04***
	(1.23)	(0.37)
Excess Bids (std)	-2.19**	0.40
	(0.88)	(0.32)
Volume (std)	3.32***	-4.39***
	(1.00)	(0.40)
Book Dummy	-1.90	0.72
	(3.20)	(1.51)
Dynamics Dummy	-0.73	0.29
	(2.74)	(1.22)
Book & Dynamics Dummy	8.54**	-3.03
	(4.27)	(1.96)
Two Insiders Dummy	0.51	4.04***
	(2.11)	(0.74)
Six Insiders Dummy	-23.19***	15.13***
	(2.21)	(0.89)
Asset Value	-0.05***	0.02***
	(0.01)	(0.00)
Constant	136.04***	35.90***
	(7.28)	(3.08)
Observations	7,494	7,494
R-squared	0.548	0.379
Chi-squared	19316	3585

Table C14. Weight forecasting accuracy as predicted by theory of mind skills (HS) and mispricing

	(1)	(2)	(3)
	Below Median MAD	Above Median MAD	All MADs
VARIABLES			
HS score (std)	**2.12**** **(0.86)**	**0.11** **(0.62)**	**2.54**** **(1.02)**
HS score (std) × MAD			**-0.01**** **(0.01)**
MAD			-0.18*** (0.01)
Male Dummy	3.70** (1.88)	1.46 (1.18)	2.64** (1.08)
Book Dummy	-0.90 (2.88)	2.13 (1.46)	0.68 (1.49)
Dynamics Dummy	-2.15 (2.41)	2.29 (1.55)	0.11 (1.21)
Book & Dynamics Dummy	-1.20 (3.62)	-4.06* (2.21)	-2.92 (1.96)
Two Insiders Dummy	-3.83*** (1.11)	3.02*** (0.94)	0.32 (0.66)
Six Insiders Dummy	14.17*** (1.10)	34.10*** (1.52)	15.51*** (0.89)
Asset Value	0.02*** (0.00)	0.01*** (0.00)	0.02*** (0.00)
Constant	63.34*** (4.58)	9.80*** (3.52)	58.66*** (3.12)
Observations	3,746	3,748	7,494
R-squared	0.111	0.187	0.365
Chi-squared	1,426	1,350	3,413

Table C15. Price forecasting error as predicted by theory of mind skills (HS) and mispricing with additional individual controls

VARIABLES	(1)	(2)	(3)
HS score (std)	**-4.04*** (1.42)**	**-0.13 (1.73)**	**-5.02*** (1.53)**
HS score (std) × MAD			**0.03** (0.01)**
MAD			0.78*** (0.01)
Male Dummy	-6.86* (3.88)	-4.82 (4.19)	-5.72** (2.87)
Book Dummy	-2.18 (4.50)	-4.14 (4.55)	-3.12 (3.13)
Dynamics Dummy	2.96 (4.58)	-8.43* (4.65)	-3.08 (2.82)
Book & Dynamics Dummy	5.81 (6.64)	15.16** (6.79)	11.10** (4.80)
Two Insiders Dummy	22.10*** (2.77)	-2.22 (2.61)	7.70*** (1.87)
Six Insiders Dummy	-10.79*** (2.73)	-101.49*** (3.67)	-20.84*** (2.24)
Intelligence score (std)	-3.47** (1.39)	-0.59 (1.68)	-2.20** (1.06)
Extraversion (std)	-0.37 (1.46)	-3.28** (1.65)	-1.93* (1.09)
Openness (std)	1.25 (1.73)	-1.48 (1.94)	0.07 (1.14)
Conscientiousness (std)	1.23 (1.64)	0.13 (1.94)	0.83 (1.00)
Agreeableness (std)	1.52 (1.39)	-1.59 (1.85)	0.02 (1.05)
Emotionality (std)	-1.69 (2.10)	-0.76 (2.11)	-0.95 (1.53)

Honesty (std)	-0.70	4.65**	1.75
	(1.61)	(2.02)	(1.20)
Risk Taking score (std)	0.86	-0.81	-0.05
	(1.43)	(1.72)	(1.12)
Stock Participation Dummy	0.61	4.95	2.92
	(4.18)	(6.04)	(3.46)
Business School Dummy	-2.96	-3.29	-2.89
	(4.57)	(4.51)	(3.11)
Humanities School Dummy	-0.90	2.65	1.03
	(6.48)	(6.01)	(4.27)
Science School Dummy	-5.05	11.73*	3.71
	(7.36)	(6.11)	(4.27)
Asset Value	-0.04***	0.04***	-0.03***
	(0.01)	(0.01)	(0.01)
Constant	44.81***	215.20***	37.00***
	(8.85)	(9.94)	(7.04)
Observations	3,746	3,748	7,494
R-squared	0.0809	0.181	0.544
Chi-squared	582.7	2,922	18,885

Table C16. Price forecasting error as predicted by theory of mind skills (HS) and mispricing with additional market controls

VARIABLES	(1)	(2)	(3)
HS score (std)	**-4.12*** (1.38)**	**-0.46 (1.84)**	**-5.27*** (1.44)**
HS score (std) × MAD			**0.03** (0.01)**
Amplitude of prices (std)	2.01*** (0.75)	81.60 (51.89)	2.31*** (0.76)
Average Price (std)	17.23*** (3.18)	-10.15*** (2.41)	9.17*** (1.23)
Excess Bids (std)	-0.28 (0.97)	-6.34*** (1.56)	-2.19** (0.88)
Volume (std)	8.50*** (1.16)	20.77*** (1.91)	3.32*** (1.00)
MAD			0.80*** (0.01)
Male Dummy	-4.70 (3.10)	-4.94 (3.92)	-4.81** (2.40)
Book Dummy	-2.15 (4.57)	-1.46 (4.51)	-1.73 (3.20)
Dynamics Dummy	3.03 (4.17)	-3.47 (4.78)	-0.33 (2.68)
Book & Dynamics Dummy	4.91 (5.94)	10.69 (6.68)	8.18* (4.30)
Two Insiders Dummy	9.06*** (3.24)	-8.60** (4.02)	0.51 (2.11)
Six Insiders Dummy	-9.33*** (2.74)	-96.28*** (5.77)	-23.20*** (2.21)
Asset Value	-0.21*** (0.04)	0.06*** (0.01)	-0.05*** (0.01)
Constant	85.14*** (12.36)	218.74*** (13.79)	41.90*** (7.04)
Observations	3,746	3,748	7,494
R-squared	0.0921	0.205	0.548
Chi-squared	640.3	2790	19961

Table C17. Price forecasting error as predicted by theory of mind skills (eye-gaze) and mispricing

VARIABLES	(1)	(2)	(3)
Eye-gaze score (std)	**-0.95**	**2.34**	**-1.08**
	(2.19)	**(1.76)**	**(2.53)**
Eye-gaze score (std) × MAD			**0.01**
			(0.02)
MAD			0.78***
			(0.01)
Male Dummy	-3.90	-4.74	-4.37*
	(3.14)	(3.95)	(2.39)
Book Dummy	-1.10	-2.49	-1.75
	(4.32)	(4.65)	(3.25)
Dynamics Dummy	3.29	-3.83	-0.40
	(4.19)	(4.69)	(2.75)
Book & Dynamics Dummy	4.84	11.21*	8.40*
	(6.00)	(6.61)	(4.30)
Two Insiders Dummy	22.12***	-2.22	7.68***
	(2.76)	(2.61)	(1.87)
Six Insiders Dummy	-10.79***	-101.50***	-20.85***
	(2.72)	(3.66)	(2.24)
Asset Value	-0.04***	0.04***	-0.03***
	(0.01)	(0.01)	(0.01)
Constant	38.52***	215.31***	34.45***
	(8.39)	(9.43)	(6.73)
Observations	3,746	3,748	7,494
R-squared	0.0732	0.177	0.542
Chi-squared	468.4	2,376	14,834

Table C18. Weight forecasting accuracy as predicted by theory of mind skills (HS), mispricing and graphical display

VARIABLES	(1) Below Median MAD & Complete Display	(2) Below Median MAD & Non-complete Display	(3) Above Median MAD & Complete Display	(4) Above Median MAD & Non-complete Display	(5) All MADs & Complete Display	(6) All MADs & Non-complete Display
HS score (std)	**2.57**	**2.12****	**-1.39**	**0.73**	**2.89**	**2.56****
	(1.78)	**(0.98)**	**(1.04)**	**(0.67)**	**(2.09)**	**(1.15)**
HS score (std) × MAD					**-0.02***	**-0.01**
					(0.01)	**(0.01)**
Male Dummy	-1.06	5.50**	0.25	2.12	-0.56	3.82***
	(3.18)	(2.26)	(1.90)	(1.33)	(2.10)	(1.26)
Book Dummy	56.69***	-0.78	14.49**	2.13	57.13***	0.76
	(8.77)	(2.86)	(5.75)	(1.42)	(5.30)	(1.46)
Dynamics Dummy		-2.07		2.16		0.12
		(2.44)		(1.54)		(1.23)
Two Insiders Dummy	-1.65	-4.39***	2.07	3.49***	0.20	0.42
	(2.17)	(1.29)	(2.40)	(0.97)	(1.41)	(0.74)
Six Insiders Dummy	13.17***	14.58***	34.81***	34.19***	15.40***	15.64***
	(1.93)	(1.30)	(2.11)	(1.84)	(1.69)	(1.06)
Asset Value	0.02**	0.01***	0.00	0.01***	0.02***	0.02***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
MAD					-0.17***	-0.19***
					(0.01)	(0.01)
Constant		65.01***		8.30**		58.43***
		(5.26)		(4.08)		(3.62)
Observations	960	2,786	960	2,788	1,920	5,574
R-squared	0.156	0.118	0.265	0.189	0.382	0.367

Table C19. Price forecasting error as predicted by theory of mind skills (HS), mispricing and graphical display with additional individual controls

VARIABLES	(1) Below Median MAD & Complete Display	(2) Below Median MAD & Non-complete Display	(3) Above Median MAD & Complete Display	(4) Above Median MAD & Non-complete Display	(5) All MADs & Complete Display	(6) All MADs & Non-complete Display
HS score (std)	**-3.28**	**-4.23****	**7.26*****	**-2.79**	**-5.32****	**-5.23*****
	(2.64)	**(1.73)**	**(2.25)**	**(1.79)**	**(2.40)**	**(1.87)**
HS score (std) × MAD					**0.07*****	**0.02**
					(0.02)	**(0.01)**
Male Dummy	13.43**	-10.89**	9.17	-9.53*	13.61***	-10.18***
	(5.26)	(4.97)	(5.61)	(4.92)	(4.75)	(3.40)
Book Dummy		-1.67		-5.84		-3.78
		(4.58)		(4.33)		(3.11)
Dynamics Dummy		3.03		-7.39		-2.52
		(4.58)		(4.93)		(2.95)
Two Insiders Dummy	22.74***	21.61***	-8.59	-0.32	5.05	8.45***
	(5.98)	(3.17)	(5.77)	(2.95)	(3.54)	(2.21)
Six Insiders Dummy	-7.53	-12.39***	-110.69***	-99.02***	-23.70***	-20.32***
	(5.59)	(3.11)	(5.34)	(4.38)	(4.61)	(2.55)
Intelligence score (std)	0.02	-3.44**	6.14***	-2.47	3.12*	-3.25***
	(2.17)	(1.62)	(2.37)	(1.67)	(1.86)	(1.12)
Extraversion (std)	0.96	-1.28	-3.08	-1.71	-0.76	-1.59
	(2.68)	(1.77)	(2.21)	(1.84)	(1.79)	(1.21)
Openness (std)	2.09	0.15	-2.15	-2.52	-0.04	-1.05
	(2.78)	(2.15)	(3.81)	(1.94)	(3.14)	(1.21)
Conscientiousness (std)	-3.11	3.05	2.23	-1.36	0.40	1.04
	(3.24)	(1.89)	(2.66)	(2.14)	(2.23)	(1.05)
Agreeableness (std)	6.08**	1.71	4.71*	-2.71	5.63***	-0.54
	(2.48)	(1.64)	(2.45)	(2.02)	(2.15)	(1.14)
Emotionality (std)	1.49	-2.53	7.20*	0.35	6.04	-1.01
	(3.34)	(2.30)	(4.13)	(2.30)	(3.72)	(1.65)
Honesty (std)	3.95	-1.55	10.28***	4.40*	8.01***	1.16
	(2.69)	(1.88)	(2.87)	(2.40)	(2.64)	(1.33)

Risk Taking score (std)	-0.35	1.16	-3.85	-0.70	-1.64	0.05
	(3.70)	(1.75)	(2.89)	(1.84)	(2.49)	(1.29)
Stock Participation Dummy	15.84	-2.51	0.71	12.75**	7.44	5.28*
	(9.72)	(4.60)	(11.49)	(5.26)	(10.36)	(3.14)
Business School Dummy	-14.59***	-1.01	18.14***	-9.18*	1.88	-4.90
	(4.75)	(5.41)	(6.74)	(4.79)	(5.90)	(3.53)
Humanities School Dummy	11.07	2.30	34.28**	0.10	25.72**	1.58
	(8.99)	(6.57)	(13.56)	(6.36)	(10.80)	(4.62)
Science School Dummy	24.15	-5.62	72.40***	8.95	47.32***	2.21
	(16.29)	(6.89)	(18.18)	(6.63)	(14.72)	(4.24)
Asset Value	-0.05*	-0.04***	0.06***	0.03***	-0.01	-0.03***
	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
MAD					0.77***	0.78***
					(0.03)	(0.02)
Constant	47.20**	42.78***	208.99***	219.98***	30.60**	39.84***
	(18.43)	(10.41)	(14.37)	(11.75)	(12.24)	(8.17)
Observations	960	2,786	960	2,788	1,920	5,574
R-squared	0.166	0.0857	0.289	0.180	0.577	0.543

Table C20. Price forecasting error as predicted by theory of mind skills (HS), mispricing and graphical display with additional market controls

VARIABLES	(1) Below Median MAD & Complete Display	(2) Below Median MAD & Non-complete Display	(3) Above Median MAD & Complete Display	(4) Above Median MAD & Non-complete Display	(5) All MADs & Complete Display	(6) All MADs & Non-complete Display
Amplitude of prices (std)	3.86***	1.53*	126.34		3.98***	1.86**
	(1.44)	(0.88)	(89.94)		(1.54)	(0.86)
Average Price (std)	13.39**	19.00***	-14.75***		3.58	10.85***
	(6.53)	(3.65)	(5.50)		(2.56)	(1.41)
Excess Bids (std)	0.03	-0.73	-4.85		-1.79	-2.48**
	(1.67)	(1.17)	(3.71)		(1.51)	(1.05)
Volume (std)	4.61*	10.05***	13.13***		-1.62	4.79***
	(2.40)	(1.32)	(3.79)		(1.66)	(1.16)
HS score (std)	**-5.80****	**-4.10****	**6.44****	**-2.65**	**-7.57*****	**-5.14*****
	(2.75)	**(1.61)**	**(3.16)**	**(1.95)**	**(2.45)**	**(1.71)**
Heider score (std) × MAD					**0.07*****	**0.02**
					(0.02)	**(0.01)**
Male Dummy	8.69*	-9.10**	-1.67	-7.16	4.05	-8.07***
	(5.19)	(3.71)	(5.47)	(4.66)	(4.47)	(2.71)
Book Dummy		-2.34		-1.57		-1.98
		(4.62)		(4.37)		(3.13)
Dynamics Dummy		2.86		-3.36		-0.36
		(4.07)		(4.79)		(2.71)
Two Insiders Dummy	10.36*	7.41*	-12.43	-0.30	1.09	0.21
	(6.20)	(3.97)	(7.57)	(2.95)	(4.08)	(2.46)
Six Insiders Dummy	-7.04	-10.96***	-108.68***	-99.04***	-24.82***	-23.08***
	(5.36)	(3.14)	(10.81)	(4.38)	(4.49)	(2.51)
Asset Value	-0.19**	-0.22***	0.08***	0.03***	-0.02	-0.06***
	(0.08)	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)
MAD					0.80***	0.80***
					(0.03)	(0.02)
Constant	82.26***	87.98***	227.82***	215.38***	40.60***	43.48***
	(26.72)	(13.67)	(21.02)	(10.72)	(12.84)	(7.93)
Observations	960	2,786	960	2,788	1,920	5,574
R-squared	0.150	0.100	0.295	0.172	0.574	0.548

Table C21. Price forecasting error as predicted by theory of mind skills, mispricing (using MAD Dummy) and graphical display

VARIABLES	(1) All MADs	(2) All MADs & Complete Display	(3) All MADs & Non-complete Display
HS score (std)	**-4.21*** (1.33)**	**-5.47** (2.60)**	**-4.25*** (1.54)**
HS score (std) × MAD Dummy	**3.97* (2.35)**	**12.22*** (3.97)**	**2.03 (2.69)**
MAD Dummy[41]	117.26*** (2.52)	117.32*** (4.49)	117.14*** (3.03)
Male Dummy	-4.77* (2.44)	4.05 (4.47)	-8.08*** (2.71)
Book Dummy	2.47 (2.19)		-1.96 (3.12)
Dynamics Dummy	3.88* (2.14)		-0.33 (2.71)
Two Insiders Dummy	7.90*** (1.89)	5.00 (3.54)	8.86*** (2.23)
Six Insiders Dummy	-47.66*** (2.19)	-49.97*** (4.30)	-47.10*** (2.53)
Asset Value	0.03*** (0.01)	0.04*** (0.01)	0.02** (0.01)
Constant	65.20*** (7.13)	70.10*** (14.19)	68.26*** (7.61)
Observations	7,494	1,920	5,574
R-squared	0.463	0.495	0.462

[41] MAD Dummy equals one if the MAD for a given market is above the median of all markets considered in the experiment and is equal to zero otherwise.

Table C22. Price forecasting error as predicted by theory of mind skills (HS), mispricing and dynamic versus static display

VARIABLES	(1) Dynamic Display	(2) Static Display
Heider score (std)	**-4.68****	**-6.15*****
	(2.16)	**(1.99)**
Heider score (std) × MAD	**0.04****	**0.01**
	(0.02)	**(0.01)**
MAD	0.76***	0.80***
	(0.02)	(0.02)
Male Dummy	-0.65	-9.60***
	(3.17)	(3.17)
Book Dummy	6.89**	-2.47
	(2.79)	(3.11)
Two Insiders Dummy	6.02**	9.24***
	(2.47)	(2.86)
Six Insiders Dummy	-22.33***	-19.77***
	(2.84)	(3.54)
Asset Value	-0.02**	-0.03***
	(0.01)	(0.01)
Constant	31.89***	39.67***
	(8.37)	(9.64)
Observations	3,838	3,656
R-squared	0.535	0.562

Table C23. Price forecasting error as predicted by theory of mind skills (HS), mispricing and graphical display

VARIABLES	(1) Below Median MAD & Complete Display	(2) Below Median MAD & Non-complete Display	(3) Above Median MAD & Complete Display	(4) Above Median MAD & Non-complete Display	(5) All MADs & Complete Display	(6) All MADs & Non-complete Display
Eye-gaze score (std)	**-0.85**	**-0.61**	**-1.77**	**2.74**	**-0.79**	**-1.07**
	(3.00)	**(2.50)**	**(1.90**	**(2.07)**	**(3.30)**	**(2.96)**
Eye-gaze score (std) × MAD					**-0.00**	**0.02**
					(0.02)	**(0.02)**
Male Dummy	7.62	-7.88**	-0.22	-6.31	4.26	-7.08**
	(5.57)	(3.71)	(5.80)	(4.80)	(4.56)	(2.77)
Book Dummy		-1.45		-2.55		-2.02
		(4.29)		(4.70)		(3.22)
Dynamics Dummy		3.05		-3.81		-0.48
		(4.09)		(4.72)		(2.76)
Two Insiders Dummy	22.58***	21.61***	-8.74	-0.31	4.88	8.42***
	(5.90)	(3.16)	(5.77)	(2.95)	(3.52)	(2.21)
Six Insiders Dummy	-7.71	-12.41***	-111.30***	-99.08***	-23.82***	-20.34***
	(5.61)	(3.10)	(5.29)	(4.38)	(4.60)	(2.55)
Asset Value	-0.05*	-0.04***	0.06***	0.03***	-0.01	-0.03***
	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
MAD					0.77***	0.78***
					(0.03)	(0.02)
Constant	46.51***	36.88***	219.94***	215.50***	39.28***	34.73***
	(17.23)	(9.58)	(14.59)	(11.05)	(11.88)	(7.57)
Observations	960	2,786	960	2,788	1,920	5,574
R-squared	0.135	0.0766	0.271	0.172	0.569	0.540

Table C24. Weight forecasting accuracy as predicted by intelligence scores and mispricing

VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs
Intelligence score (std)	**1.65***	**0.04**	**2.01***
	(0.98)	**(0.53)**	**(1.20)**
Intelligence (std) × MAD			**-0.01**
			(0.01)
MAD			-0.18***
			(0.01)
Male Dummy	3.61*	1.44	2.61**
	(1.85)	(1.22)	(1.08)
Book Dummy	-0.91	2.12	0.69
	(2.90)	(1.47)	(1.52)
Dynamics Dummy	-2.21	2.29	0.08
	(2.47)	(1.55)	(1.24)
Book & Dynamics Dummy	-1.89	-4.08*	-3.30*
	(3.61)	(2.23)	(1.98)
Two Insiders Dummy	-3.83***	3.02***	0.32
	(1.11)	(0.94)	(0.65)
Six Insiders Dummy	14.17***	34.10***	15.51***
	(1.10)	(1.52)	(0.89)
Asset Value	0.02***	0.01***	0.02***
	(0.00)	(0.00)	(0.00)
Constant	64.71***	9.90***	59.12***
	(4.43)	(3.53)	(3.07)
Observations	3,746	3,748	7,494
R-squared	0.109	0.187	0.364
Chi-squared	1411	1,355	3,478

Table C25. Price forecasting error as predicted by intelligence scores and mispricing with additional individual controls

VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs
Intelligence score (std)	**-3.47****	**-0.59**	**-3.87****
	(1.39)	**(1.68)**	**(1.73)**
Intelligence (std) × MAD			**0.01**
			(0.01)
MAD			0.78***
			(0.01)
Male Dummy	-6.86*	-4.82	-5.72**
	(3.88)	(4.19)	(2.87)
Book Dummy	-2.18	-4.14	-3.13
	(4.50)	(4.55)	(3.13)
Dynamics Dummy	2.96	-8.43*	-3.08
	(4.58)	(4.65)	(2.82)
Book & Dynamics Dummy	5.81	15.16**	11.11**
	(6.64)	(6.79)	(4.80)
Two Insiders Dummy	22.10***	-2.22	7.69***
	(2.77)	(2.61)	(1.87)
Six Insiders Dummy	-10.79***	-101.49***	-20.84***
	(2.73)	(3.67)	(2.24)
Heider score (std)	-4.04***	-0.13	-1.95*
	(1.42)	(1.73)	(1.11)
Extraversion (std)	-0.37	-3.28**	-1.93*
	(1.46)	(1.65)	(1.09)
Openness (std)	1.25	-1.48	0.07
	(1.73)	(1.94)	(1.14)
Conscientiousness (std)	1.23	0.13	0.83
	(1.64)	(1.94)	(1.00)
Agreeableness (std)	1.52	-1.59	0.02
	(1.39)	(1.85)	(1.04)
Emotionality (std)	-1.69	-0.76	-0.95
	(2.10)	(2.11)	(1.53)

Honesty (std)	-0.70	4.65**	1.75
	(1.61)	(2.02)	(1.20)
Risk Taking score (std)	0.86	-0.81	-0.05
	(1.43)	(1.72)	(1.12)
Stock Participation Dummy	0.61	4.95	2.93
	(4.18)	(6.04)	(3.46)
Business School Dummy	-2.96	-3.29	-2.89
	(4.57)	(4.51)	(3.11)
Humanities School Dummy	-0.90	2.65	1.03
	(6.48)	(6.01)	(4.27)
Science School Dummy	-5.05	11.73*	3.71
	(7.36)	(6.11)	(4.27)
Asset Value	-0.04***	0.04***	-0.03***
	(0.01)	(0.01)	(0.01)
Constant	44.81***	215.20***	37.60***
	(8.85)	(9.94)	(7.06)
Observations	3,746	3,748	7,494
R-squared	0.0809	0.181	0.544
Chi-squared	582.7	2922	20293

Table C26. Price forecasting error as predicted by intelligence scores and mispricing with additional market controls

VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs
Intelligence score (std)	**-3.17****	**-1.24**	**-4.00****
	(1.46)	**(1.64)**	**(1.83)**
Intelligence (std) × MAD			**0.01**
			(0.01)
Amplitude of prices (std)	2.01***	81.54	2.31***
	(0.75)	(51.89)	(0.76)
Average Price (std)	17.24***	-10.16***	9.17***
	(3.17)	(2.41)	(1.23)
Excess Bids (std)	-0.27	-6.34***	-2.18**
	(0.97)	(1.56)	(0.88)
Volume (std)	8.49***	20.77***	3.32***
	(1.16)	(1.91)	(1.00)
MAD			0.80***
			(0.01)
Male Dummy	-4.53	-5.11	-4.85**
	(3.01)	(4.04)	(2.33)
Book Dummy	-2.14	-1.61	-1.83
	(4.62)	(4.51)	(3.27)
Dynamics Dummy	3.13	-3.44	-0.26
	(4.29)	(4.77)	(2.73)
Book & Dynamics Dummy	6.24	11.15*	9.12**
	(5.95)	(6.71)	(4.32)
Two Insiders Dummy	9.09***	-8.59**	0.52
	(3.24)	(4.02)	(2.11)
Six Insiders Dummy	-9.32***	-96.28***	-23.20***
	(2.74)	(5.77)	(2.21)
Asset Value	-0.21***	0.06***	-0.05***
	(0.04)	(0.01)	(0.01)
Constant	82.75***	218.27***	40.99***
	(12.10)	(13.71)	(6.87)
Observations	3,746	3,748	7,494
R-squared	0.0907	0.205	0.548
Chi-squared	677.7	2893	20165

Table C27. Price forecasting error as predicted by intelligence score, extraversion and mispricing (using MAD Dummy)

VARIABLES	(1) All MADs	(2) All MADs
Intelligence score (std)	**-3.40**** **(1.60)**	
Intelligence (std) × MAD Dummy	**0.01** **(0.01)**	
Extraversion (std)		**-1.20** **(1.36)**
Extraversion (std) × MAD Dummy		**-2.32** **(2.13)**
MAD Dummy[42]	117.26*** (2.53)	117.27*** (2.52)
Male Dummy	-4.75** (2.38)	-4.01* (2.35)
Book Dummy	2.84 (2.18)	2.67 (2.17)
Dynamics Dummy	4.39** (2.18)	3.36 (2.18)
Two Insiders Dummy	7.90*** (1.89)	7.90*** (1.89)
Six Insiders Dummy	-47.66*** (2.19)	-47.66*** (2.19)
Asset Value	0.03*** (0.01)	0.03*** (0.01)
Constant	63.99*** (6.93)	64.02*** (6.91)
Observations	7,494	7,494
R-squared	0.463	0.463

[42] MAD Dummy equals one if the MAD for a given market is above the median of all markets considered in the experiment and is equal to zero otherwise.

Table C28. Price forecasting error as predicted by CRT scores and mispricing with additional market controls

VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs	(4) All MADs
CRT score (std)	**-3.29****	**0.19**	**-4.23*****	**-3.10***
	(1.35)	**(1.56)**	**(1.61)**	**(1.68)**
HS score (std)				**-4.50*****
				(1.50)
CRT score (std) × MAD			**0.02****	**0.02**
			(0.01)	**(0.01)**
HS score (std) × MAD				**0.02***
				(0.01)
MAD			0.78***	0.78***
			(0.01)	(0.01)
Male Dummy	-3.43	-4.81	-4.16*	-4.61*
	(3.03)	(3.96)	(2.40)	(2.43)
Book Dummy	-2.98	-1.28	-2.11	-2.16
	(4.64)	(4.43)	(3.28)	(3.18)
Dynamics Dummy	2.30	-3.40	-0.70	-0.60
	(4.12)	(4.74)	(2.71)	(2.68)
Book & Dynamics Dummy	7.10	10.67	9.29**	8.89**
	(6.07)	(6.60)	(4.33)	(4.38)
Two Insiders Dummy	22.12***	-2.22	7.69***	7.69***
	(2.76)	(2.61)	(1.87)	(1.87)
Six Insiders Dummy	-10.80***	-101.49***	-20.85***	-20.85***
	(2.72)	(3.67)	(2.24)	(2.24)
Asset Value	-0.04***	0.04***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	41.03***	213.13***	34.43***	35.35***
	(8.20)	(9.23)	(6.64)	(6.62)
Observations	3,746	3,748	7,494	7,494
R-squared	0.0752	0.176	0.543	0.543
Chi-squared	480.9	2285	16639	16945

Table C29. Weight forecasting accuracy as predicted by extraversion scores and mispricing

VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs
Extraversion (std)	**1.66***	**0.21**	**2.42****
	(0.97)	**(0.56)**	**(1.12)**
Extraversion (std) × MAD			**-0.01***
			(0.01)
MAD			-0.18***
			(0.01)
Male Dummy	3.05*	1.41	2.28**
	(1.85)	(1.19)	(1.05)
Book Dummy	-1.20	2.11	0.52
	(2.91)	(1.47)	(1.53)
Dynamics Dummy	-1.88	2.33	0.28
	(2.44)	(1.55)	(1.21)
Book & Dynamics Dummy	-1.08	-4.04*	-2.84
	(3.63)	(2.20)	(1.95)
Two Insiders Dummy	-3.83***	3.02***	0.32
	(1.11)	(0.94)	(0.66)
Six Insiders Dummy	14.17***	34.10***	15.50***
	(1.10)	(1.52)	(0.89)
Asset Value	0.02***	0.01***	0.02***
	(0.00)	(0.00)	(0.00)
Constant	64.72***	9.91***	59.23***
	(4.37)	(3.53)	(3.02)
Observations	3,746	3,748	7,494
R-squared	0.109	0.187	0.364
Chi-squared	1384	1428	3491

Table C30. Price forecasting error as predicted by extraversion scores and mispricing with additional individual controls

VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs
Extraversion (std)	**-0.37**	**-3.28****	**-1.05**
	(1.46)	**(1.65)**	**(1.77)**
Extraversion (std) × MAD			**-0.01**
			(0.01)
MAD			0.78***
			(0.01)
Male Dummy	-6.86*	-4.82	-5.72**
	(3.88)	(4.19)	(2.87)
Book Dummy	-2.18	-4.14	-3.12
	(4.50)	(4.55)	(3.13)
Dynamics Dummy	2.96	-8.43*	-3.07
	(4.58)	(4.65)	(2.82)
Book & Dynamics Dummy	5.81	15.16**	11.10**
	(6.64)	(6.79)	(4.80)
Two Insiders Dummy	22.10***	-2.22	7.69***
	(2.77)	(2.61)	(1.87)
Six Insiders Dummy	-10.79***	-101.49***	-20.84***
	(2.73)	(3.67)	(2.24)
Intelligence score (std)	-3.47**	-0.59	-2.20**
	(1.39)	(1.68)	(1.06)
Heider score (std)	-4.04***	-0.13	-1.95*
	(1.42)	(1.73)	(1.11)
Openness (std)	1.25	-1.48	0.07
	(1.73)	(1.94)	(1.14)
Conscientiousness (std)	1.23	0.13	0.83
	(1.64)	(1.94)	(1.00)
Agreeableness (std)	1.52	-1.59	0.02
	(1.39)	(1.85)	(1.04)

Emotionality (std)	-1.69	-0.76	-0.95
	(2.10)	(2.11)	(1.53)
Honesty (std)	-0.70	4.65**	1.75
	(1.61)	(2.02)	(1.20)
Risk Taking score (std)	0.86	-0.81	-0.05
	(1.43)	(1.72)	(1.12)
Stock Participation Dummy	0.61	4.95	2.92
	(4.18)	(6.04)	(3.46)
Business School Dummy	-2.96	-3.29	-2.89
	(4.57)	(4.51)	(3.11)
Humanities School Dummy	-0.90	2.65	1.03
	(6.48)	(6.01)	(4.27)
Science School Dummy	-5.05	11.73*	3.71
	(7.36)	(6.11)	(4.27)
Asset Value	-0.04***	0.04***	-0.03***
	(0.01)	(0.01)	(0.01)
Constant	44.81***	215.20***	37.37***
	(8.85)	(9.94)	(7.05)
Observations	3,746	3,748	7,494
R-squared	0.0809	0.181	0.544
Chi-squared	582.7	2922	18114

Table C31. Price forecasting error as predicted by extraversion scores and mispricing with additional market controls

VARIABLES	(1) Below Median MAD	(2) Above Median MAD	(3) All MADs
Amplitude of prices (std)	2.01***	81.51	2.31***
	(0.75)	(51.90)	(0.76)
Average Price (std)	17.24***	-10.17***	9.17***
	(3.18)	(2.41)	(1.23)
Excess Bids (std)	-0.27	-6.33***	-2.18**
	(0.97)	(1.56)	(0.88)
Volume (std)	8.50***	20.78***	3.32***
	(1.16)	(1.91)	(1.00)
Extraversion (std)	**-0.59**	**-3.87****	**-1.42**
	(1.41)	**(1.62)**	**(1.69)**
Extraversion (std) × MAD			**-0.01**
			(0.01)
MAD			0.80***
			(0.01)
Male Dummy	-3.79	-4.33	-4.06*
	(3.17)	(3.78)	(2.31)
Book Dummy	-1.58	-1.36	-1.41
	(4.71)	(4.47)	(3.28)
Dynamics Dummy	2.97	-4.18	-0.72
	(4.29)	(4.60)	(2.71)
Book & Dynamics Dummy	5.03	10.17	7.96*
	(6.14)	(6.48)	(4.28)
Two Insiders Dummy	9.08***	-8.58**	0.51
	(3.24)	(4.02)	(2.11)
Six Insiders Dummy	-9.32***	-96.25***	-23.20***
	(2.74)	(5.77)	(2.21)
Asset Value	-0.21***	0.06***	-0.05***
	(0.04)	(0.01)	(0.01)
Constant	82.42***	218.37***	40.73***
	(12.19)	(13.54)	(6.93)
Observations	3,746	3,748	7,494
R-squared	0.0886	0.207	0.548
Chi-squared	606.3	2860	19907

Table C32. Price forecasting error as predicted by individual characteristics and two information structures (data for 6-*fully informed* markets are excluded)

VARIABLES	(1)	(2)	(3)
Intelligence score (std)	**-0.48**		
	(1.58)		
Intelligence score × Two Insiders Dummy	**-1.41**		
	(2.21)		
HS score (std)		**-1.50**	
		(1.58)	
HS score × Two Insiders Dummy		**0.64**	
		(2.04)	
Extraversion (std)			**-1.24**
			(1.22)
Extraversion × Two Insiders Dummy			**-1.41**
			(1.87)
Male Dummy	-3.00	-3.00	-2.48
	(2.36)	(2.33)	(2.29)
Book Dummy	2.41	2.46	2.64
	(3.00)	(2.95)	(2.99)
Dynamics Dummy	0.53	0.50	0.14
	(2.86)	(2.85)	(2.85)
Book & Dynamics Dummy	5.29	4.79	4.59
	(4.03)	(4.06)	(4.01)
Two Insiders Dummy	15.22***	15.22***	15.22***
	(1.94)	(1.94)	(1.94)
Asset Value	0.14***	0.14***	0.14***
	(0.01)	(0.01)	(0.01)
Constant	99.48***	100.52***	99.65***
	(11.16)	(11.34)	(11.20)
Observations	4,994	4,994	4,994
R-squared	0.0748	0.0748	0.0750

Appendix D. Predictions of CRT composition of markets and distribution of private information

All linear panel regressions use robust standard errors in parentheses with session and time fixed effects. (std) indicates a standardized variable.
We denote: *** p<0.01, ** p<0.05, * p<0.1

<u>CRT predictions</u>

We define the dependent variable "CRT correct" as the weight in percent a forecaster assigned to the category (i.e., 0 to 4, 5 to 8, and 9 to 12) that includes the correct number of high-CRT traders in the observed block of markets.

Table D1. CRT correct as a function of individual characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Intelligence score (std)	1.25** (0.60)					1.01 (0.62)
CRT score (std)		1.04 (0.64)				0.52 (0.64)
HS score (std)			0.53 (0.71)			0.33 (0.62)
Eye-gaze score (std)				0.79 (0.98)		0.51 (0.90)
Extraversion (std)					-0.02 (0.66)	0.02 (0.63)
Male Dummy	0.53 (1.26)	0.13 (1.30)	0.36 (1.28)	0.34 (1.25)	0.23 (1.31)	0.58 (1.27)
Book Dummy	1.18 (1.81)	1.42 (1.86)	1.06 (1.85)	0.57 (1.72)	1.03 (1.84)	1.06 (1.70)
Dynamics Dummy	2.02 (1.64)	2.30 (1.69)	2.06 (1.67)	1.85 (1.58)	2.09 (1.74)	1.95 (1.60)
Book & Dynamics Dummy	-4.70** (2.37)	-4.91** (2.41)	-4.25* (2.35)	-4.06* (2.28)	-4.32* (2.35)	-4.71** (2.25)
Two Insiders Dummy	-0.62 (1.51)	-0.62 (1.51)	-0.62 (1.51)	-0.62 (1.51)	-0.62 (1.51)	-0.62 (1.52)

Six Insiders Dummy	-4.22**	-4.22**	-4.22**	-4.22**	-4.22**	-4.22**
	(1.67)	(1.67)	(1.67)	(1.67)	(1.67)	(1.67)
Asset Value	-0.01**	-0.01**	-0.01**	-0.01**	-0.01**	-0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	41.41***	40.97***	41.15***	42.18***	41.49***	41.40***
	(3.42)	(3.51)	(3.49)	(3.48)	(3.51)	(3.36)
Observations	1,512	1,512	1,512	1,512	1,512	1,512
R-squared	0.0192	0.0184	0.0172	0.0177	0.0168	0.0204
Chi-squared	42.06	37.48	36.66	35.03	35.51	44.56

Information distribution predictions

We define the dependent variable "Correct Information Distribution" as the weight in percent a forecaster assigned to the correct distribution of private information in the observed block of markets (i.e., 12-*partially informed*, 6-*fully informed*, and 2-*fully informed*).

Table D2. Correct Information Distribution a function of individual characteristics

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Intelligence score (std)	**-2.00****					**-1.61***
	(0.95)					**(0.91)**
CRT score (std)		**-0.40**				**-0.58**
		(0.94)				**(0.88)**
HS score (std)			**2.13****			**2.79*****
			(1.08)			**(1.05)**
Eye-gaze score (std)				**-1.46***		**-1.60****
				(0.76)		**(0.70)**
Extraversion (std)					**-2.19****	**-2.71*****
					(0.93)	**(0.92)**
Male Dummy	1.29	1.81	2.32	1.56	2.06	2.27
	(2.25)	(2.26)	(2.19)	(2.23)	(2.18)	(2.06)
Book Dummy	1.25	1.35	1.60	2.36	1.56	2.25
	(2.69)	(2.78)	(2.76)	(2.74)	(2.68)	(2.74)
Dynamics Dummy	2.74	2.52	2.44	3.07	2.02	2.19
	(3.01)	(3.11)	(3.09)	(3.12)	(3.06)	(2.85)
Book & Dynamics Dummy	1.28	0.90	0.94	0.19	0.36	0.95
	(3.88)	(3.93)	(3.84)	(3.87)	(3.83)	(3.66)
Two Insiders Dummy	1.22	1.22	1.22	1.22	1.22	1.22
	(2.08)	(2.08)	(2.08)	(2.08)	(2.08)	(2.09)
Six Insiders Dummy	4.80**	4.80**	4.80**	4.80**	4.80**	4.80**
	(2.01)	(2.01)	(2.01)	(2.01)	(2.01)	(2.01)
Asset Value	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	33.27***	33.36***	31.72***	31.90***	33.15***	30.33***
	(4.39)	(4.53)	(4.77)	(4.66)	(4.27)	(4.49)
Observations	1,512	1,512	1,512	1,512	1,512	1,512
R-squared	0.0232	0.0194	0.0236	0.0212	0.0238	0.0361
Chi-squared	34.43	28.58	31.21	29.21	34.49	48.47

Table D3. Correct Information Distribution a function of individual characteristics

SAMPLE	(1) 6-*fully informed* markets	(2) 2-*fully informed* markets	(3) 12-*partially informed* markets	(4) 12-*partially informed* & 2-*fully informed* markets
DEPENDENT VARIABLE	Correct Information Distribution			Prediction weight (12-*partially informed*)[43]
Intelligence score (std)	-0.10	-1.28	-3.64**	-0.56
	(1.50)	(1.41)	(1.60)	(1.38)
CRT score (std)	-2.62*	0.19	0.27	0.14
	(1.51)	(1.34)	(1.83)	(1.37)
HS score (std)	**6.23*** **	**1.77**	**0.60**	**1.46**
	(1.63)	**(1.51)**	**(2.07)**	**(1.54)**
Eye-gaze score (std)	-1.57	-0.89	-2.45	-1.06
	(1.31)	(1.47)	(1.73)	(1.44)
Extraversion (std)	**-4.29*** **	**-0.91**	**-3.27** **	**-3.31*** **
	(1.38)	**(1.44)**	**(1.53)**	**(1.21)**
Male Dummy	3.30	-0.02	4.03	4.63*
	(3.15)	(2.82)	(3.44)	(2.61)
Book Dummy	13.26***	-11.70***	4.05	7.93**
	(4.36)	(3.67)	(4.83)	(3.98)
Dynamics Dummy	8.43*	-5.64	3.15	2.33
	(4.82)	(3.51)	(5.06)	(3.56)
Book & Dynamics Dummy	-10.42*	14.90***	-0.38	-7.57
	(6.06)	(5.26)	(6.55)	(5.01)
Asset Value	0.01	-0.01	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	34.03***	33.41***	30.64***	29.04***
	(7.14)	(6.12)	(7.47)	(4.89)
Observations	504	504	504	1,008
R-squared	0.0867	0.0599	0.0702	0.0406
Chi-squared	58.61	47.69	38.94	59.43

[43] This is the weight in percent assigned to the 12-*partially informed* market category.